MEASURING THE IMPACT OF PROGRAMMED DEPOT MAITENANCE FUNDING SHORTFALLS ON WEAPON SYSTEM AVAILABILITY

THESIS

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THESIS

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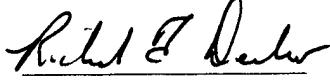
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<div align="right">Donald F. Hurry</div>

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Abstract

This study used the Poisson regression technique, bootstrap estimates, and the

Kaplan-Meier estimates for survivor curves to determine the impact of Programmed

Depot Maintenance (PDM) on weapon system availability. More specifically, these

techniques estimated the effect in the number failures per year due to PDM, but the

bootstrap technique also estimated the effect in the amount of downtime experienced by a

weapon system due to PDM. Although the Poisson regression model did not pass the

rigors of statistical testing, the Poisson regression suggested differences in the number of

failures per year between PDM and no-PDM weapon systems. The results of the

bootstrap estimates for the number of failures per year and amount of downtime per year

showed that the no-PDM weapon systems experienced approximately 1.3 failures per year

while remaining unserviceable approximately 120 days per year, and PDM weapon

systems experienced approximately .3 failures per year while remaining unserviceable

approximately 30 days per year. PDM reduced the number of failures per year and

drastically reduced weapon system downtime per year. PDM increased weapon system

availability from approximately 67 percent to approximately 92 percent.

MEASURING THE IMPACT OF PDM FUNDING SHORTFALLS ON WEAPON SYSTEM AVAILABILITY

I. Introduction

All systems, whether in the Department of the Defense (DoD) weapon system inventory or not, eventually fail. Early in a weapon system's life cycle, these failures are relatively minor and can be quickly repaired at the base level. However, as a weapon system ages, failures can occur more frequently. The probability of a major failure, which can not be repaired at base level, also increases. To minimize the effects of age and major failures of a weapon system, the DoD developed Programmed Depot Maintenance (PDM). "The Department of Defense Dictionary of Military and Associated Terms defines depot maintenance as '...maintenance performed on materiel requiring major overhaul or a complete rebuild of parts, assemblies, subassemblies, and end items, including the manufacture of parts, modifications, testing, and reclamation as required'" (Joint Logistic Commanders, 1988:14). When the weapon system leaves the depot, it is considered, for all intents and purposes, a brand new weapon system.

Unfortunately, PDM is a very expensive process and "across the services represents an approximately $10 billion dollars a year business" (Joint Logistic Commanders, 1988:11). "Both the House Appropriations Committee (HAC) and the Senate Appropriations Committee (SAC) have questioned the credibility of the depot maintenance requirements as reflected in the President's Budget and have expressed this concern in the FY89 budget markup" (Joint Logistic Commanders, 1988:12).

The HAC and SAC believe that there is a hierarchy of maintenance functions and that there should be an emphasis to perform maintenance at the lowest level (Joint Logistic Commanders, 1988:11). This philosophy threatens the DoD budget for PDM. The DoD is concerned because the DoD believes PDM increases the weapon system availability. This study will attempt to quantify the increase in a weapon system's availability due to PDM. Chapter 1 will provide the motivation for the study and the PDM budget process, explain the concept of PDM, provide a brief problem statement and present the scope of the data.

Background

The current methodology for determining PDM funding within the DoD does not effectively relate requirements to readiness (Bachmann, 1994:21). As a result, the degradation of readiness or sustainability because of shortfalls in depot maintenance funding has not been quantified (Bachmann, 1994:21). In order to justify Congressional funding for PDM, the DoD needs to develop a model with the capability to link resource allocation to actual unit readiness and then readiness directly to PDM funding. Currently, no standardized model exists among the Services. This creates a major problem in prioritizing weapon system funding between Services. A top down modeling effort can address this shortfall. More specifically, a model must be conceived that formally addresses the problem of linking unit readiness to PDM funding. Furthermore, this model must be robust and easily applied to other weapon systems (Byrd, 1994: 1). This study will attempt to illustrate the importance of PDM for a test case and develop a more comprehensive architecture for relating readiness to PDM funding shortfalls that can be applied across all the Services.

The DoD uses a variety of quantitative and qualitative resource measures to indicate unit readiness, but they primarily focus on Status Of Resource and Training Systems (SORTS) (C-ratings) and Mission Capable (MC) rates of weapon systems (JGLR-DMBA sub group meeting). SORTS measures the "month to month readiness of personnel, equipment, and training of operational forces" (Curtin, 1994:1). It ranges from a fully mission capable status of C-1 to a not mission capable status of C-4 with C-5 indicating unit deactivation. This measure targets an organization's availability and capability to fight, but does not capture the availability of an entire inventory of a weapon system. Therefore, SORTS can not be used to determine the allocation of PDM funding.

MC rate is defined as: The "number of items in maintenance over a set number of days" (Gebicke, 1995:8). This is a good indicator for weapon system availability, but gives no insight on variability of the downtime distribution. Because of the variety of missions subjected to the different weapon systems, as well as the differences inherent in each weapon system's failure distributions, the downtime distributions are presumably different for each weapon system. In addition, each distribution may have a unique variance. Depending on the actual downtime distribution of a weapon system, the variability of the distribution can be quite large, and therefore it can be difficult to compare MC rates across different weapon systems. Because of these difficulties, the DoD should not solely depend on MC rates for the allocation of PDM funding.

When dealing with readiness, the Commanders-in-Chief focus on their Critical Items List (CIL) (The Readiness Impacts of Depot Maintenance UDR, 1994:10). The CIL consists of essential weapon systems, as seen by the respective CINC, to conduct a war fighting operation. This list is limited to 120 end items (The Readiness Impacts of Depot Maintenance UDR, 1994:10). The Joint Chiefs of Staff then compile all of these lists and develop a composite list,

the composite CINC CIL, of 150 items. This study will attempt to provide a framework to analyze the relationship between shortfalls in PDM funding and equipment availability that can be applied to all items on the CINC CIL.

The DoD tracks depot maintenance funding with depot maintenance backlog dollars and percentage of requirements funded. Backlog equates to Unfunded Deferred Requirements (UDR). In the Air Force, each depot forecasts a total requirement for each weapon system for the next fiscal year. Other services rely on inputs from Type Command or Combat Command. Unfortunately, the total requirement can not be serviced within that fiscal year due to operational commitments, capability requirements, and other unexecutable requirements. The total requirement minus the prior operational commitments, capability requirements and other unexecutable requirements is the executable requirement. The difference between the executable requirement and the funded requirement is the UDR (Bachmann, 1994:10). This study will attempt to provide the framework to assess weapon system availability that can be used to justify PDM funding for the UDR.

Programmed Depot Maintenance

PDM is one of the maintenance activities under the concept of Reliability Centered Maintenance (RCM) which all DoD agencies are required to follow in accordance with Defense Directive 4151.16 (Love, 1971:3). The goal of the RCM program is to identify potential failures and to perform maintenance activities to prevent the failure. The maintenance activities include:

1. Scheduled inspection of an item at regular intervals to find any potential failures.
2. Scheduled rework of an item at or before some specified age limit.
3. Scheduled discard of an item at or before some specified life lime.

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4. Scheduled inspection of a hidden function item to find functional failures.

<div align="right">(Love, 1971:8)</div>

These actions will reduce the risk of catastrophic failures of a weapon system while decreasing the downtime due to corrective maintenance in the field.

The program begins with an in-depth failure analysis of each the weapon system's major components. The analysis utilizes both engineering data as well as operational history. A failure in these components is then categorized as either an "operational, safety, or economic consequence" (Love, 1971:6). The failure is further categorized as:

1. Catastrophic: A failure which may cause death or weapon system loss.
2. Critical: A failure which may cause severe injury, major property loss, or major system damage which will result in mission loss.
3. Marginal: A failure which may cause minor injury, property damage or minor system damage which will result in delay, loss of availability or mission degradation.
4. Minor: A failure not serious enough to cause injury, property damage or system damage, but which will result in unscheduled maintenance repair (corrective maintenance).

<div align="right">(Love, 1971:10)</div>

Maintenance actions are then scheduled to assess the failure data to minimize the consequences of failure. PDM deals primarily with catastrophic and critical failures, but is also scheduled at specific points in the life of a weapon system (mid-life rebuild).

Problem

This study will attempt to quantify the decrease in weapon system availability in the field resulting from shortfalls in PDM funding. The downtime, or unavailability, of a weapon system can be broken down into two distinct components. First, the weapon system experiences a failure. Then, the weapon system is out of service due to repair. There will be two different approaches used to model these components.

<div align="center">5</div>

First, a Poisson regression model, using historical failure data of the Marine Corps' Logistic Vehicle System (LVS) will be used to attempt to predict the expected number of failures per year. Failures will be broken out by the manufacturing year of the vehicle for the LVS and PDM or no-PDM status.

Second, a non-parametric approach, called the bootstrap technique, will be used to estimate the expected downtime per year for each category of the LVS. The bootstrap technique samples the empirical time-to-failure distribution to obtain a failure time. It then samples the empirical service time distribution to obtain a service time. This is repeated until the simulation clock reaches 365 days. The empirical distributions are estimated using the Kaplan-Meier technique (Leemis, 1995:257). The methodologies for both approaches are further developed in Chapter 3.

Scope

This study will focus only on the PDM program of depot maintenance. The analysis will be conducted on the failure data of the Marine Corps' LVS. The LVS truck data consists of 5 years of failure data (field repair only) and does not include depot repair. It was extracted from the Marine Corps' Integrated Maintenance Management System's (MIMMS) data base. The other data sources from the LVS truck include data obtained from the depot weapon system equipment manager and Oshcosh, the manufacturer of the LVS.

II. Literature Review

Recent literature indicates that there are several studies and mathematical models which provide insight into the degradation of readiness due to depot maintenance shortfalls. The Air Force Funding Availability Multi-Method Allocator for Spares (FAMMAS) modeled the decrease in availability due to PDM shortfalls on a component level with aircraft. Synergy Incorporated proposed a methodology to model aircraft availability proposing a Monte Carlo simulation. A study, "Depot Maintenance in the Air Force: How Requirements are Determined and How They Relate to Aircraft Readiness and Sustainability," modeled availability of aircraft, while deployed in a combat scenario, with shortfalls in the War Reserve Materiel Kits (WRSK) due to lack of PDM funding. Other studies calculated the optimal PDM cycle which minimizes the total life-cycle cost of the weapon system. They include: The Army's Bradley Fighting Vehicle Study and the Army's M1-IP Tank Study. A thesis by Kephart and Roberts, "Aligning Demand for Spare Parts with their Underlying Failures Modes," modeled the number of demands using multiple linear regression and a Poisson process, for aircraft reparables at the work unit code level. Finally, the bootstrap method offered a non-parametric approach to estimate the number of failures per year and the downtime per year using empirical failure distributions.

FAMMAS

The FAMMAS model assesses readiness impacts of unfunded depot maintenance. It is based on major component availability, including parts procurement and initial spares funding. FAMMAS focuses more on the exchangeable component repair program and not the PDM

program. It illustrates the past four years, the current year, and projects three future funding years to accurately model actual dollars with procurement lags. There can be several years between a component's order time and receipt time. This is used to develop the funded requirements / total requirements ratio for the projected years. FAMMAS utilizes the following availability marginal return model:

$$y = 1 - ae^{-bx}$$

where

y = weapon system availability

x = funding ratio

a, b are model constants

(FAMMAS:4-23)

When using this model, the "marginal return curves for funding vs. availability should incorporate simultaneous treatment of buy, repair, and initial spares funding and requirements" (FAMMAS: 4-22).

FAMMAS requires both the historical Total Non Mission Capable rate due to Supply (TNMCS) and the historical Non Mission Capable rate due Maintenance (NMCM) for the weapon system. NMCM rates are used in a time series model to predict a mission capable rate. The TNMCS rate calibrates the marginal return curve for the weapon system. FAMMAS fits two points to obtain the constants for this model.

FAMMAS utilizes the linear relationship of 1 - TNMCS and aircraft availability, which is output from the Air Force's Aircraft Availability Model (AAM). The AAM determines the availability of an aircraft type by considering the availability of its specific components. Availability ranges from zero (not available) to one (always available). All the components are

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considered to work independently, therefore aircraft availability is the product of its component's availability.

The AAM prioritizes the buy for the given funding level and "buys" the components which maximizes aircraft availability. Components are repaired or procured only when they increase aircraft availability. Therefore, when funding decreases, component availability decreases, which in return, decreases weapon system availability. When this relationship is represented as a general linear model, the regression constant will be the availability with no funding, which is the first point. The second point is the base year availability value and funding ratio. This exponential relationship reflects a marginal decrease in availability as the funding ratio decreases and exhibits diminishing returns as the ratio increases. This model deals with a weapon system at the component level and can not be applied to all weapon systems in the DoD inventory.

Synergy Incorporated

Synergy Incorporated, an analysis company located in Washington D.C., did a preliminary study on the UDR problem and developed a proposed methodology to solve this problem. This study was never funded. The plan, "A Discussion of Modeling Support for PDM Analyses and Assessments," proposed a Monte Carlo simulation to determine if PDM did impact readiness and weapon system sustainability. If PDM did impact readiness and weapon system sustainability, Synergy wanted to generalize, quantify, and credibly project PDM's effect (Synergy, 1994:1). "If useful and verifiable quantification is achieved, can it be codified and incorporated into a decision support architecture and used to defend PDM" (Synergy, 1994:1)?

Synergy's approach to define the relationship of PDM shortfalls and MC rates involves several steps. First, Synergy creates a critical item list (depot critical items) and models each

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item's failure rate, estimating the Weibull failure distribution parameters for each critical component. Next, Synergy will perform a Monte Carlo study to estimate aircraft failure rate due to each PDM critical components without PDM. This "increase" in the failure rate will then be translated into TNMCS and NMCM rates. Synergy "anticipates using regression analysis on time series data to quantify relationships between PDM work performed and weapon system performance " (Synergy, 1994:9). Finally, they will combine these rates with overall rates from a model like the FAMMAS model (Synergy, 1994: 18). Like the FAMMAS model, this approach deals with a weapon system at the component level and can not be applied to all the weapon system's the DoD's inventory.

Depot Maintenance in the Air Force: How Requirements are Determined and How They Relate to Aircraft Readiness and Sustainability

O'Malley and Bachman of the Logistics Management Institute performed a study on aircraft availability with respect to a shortage of serviceable spare parts. In 1987, large cuts in Depot Purchased Equipment Maintenance prompted this study, but it focused on the exchangeable component repair program and not the PDM program (DPEM) (O'Malley and Bachman, 1990:A-3). They studied an F-16A 24-aircraft squadron and an F-111D 18-aircraft squadron. Each squadron was analyzed independently and the study was limited to stock numbers in the WRSK kits. In order to get two years of projected parts for depot return, they analyzed the D041 (component peacetime factors) and each squadron's flying hour program (O'Malley and Bachman, 1990:3-2). As with the FAMMAS model, they then used the AAM to prioritize the parts repair, but only used a fraction of the total funding level to repair all the parts, to maximize aircraft availability. They used the Dyna-METRIC (Dynamic Multi-Echelon

Technique for Recoverable Item Control) to evaluate the resulting degradation of availability in the scenario that the squadron deployed with a depleted WRSK kit (O'Malley and Bachman, 1990:3-3). They found that each WRSK kit could support the planned sortie generation for both nominal scenarios (O'Malley and Bachman, 1990:A-6). This model dealt with weapon system component spares and estimated the availability of aircraft in the field with a depleted WRSK kit. PDM funding for spares was not addressed in this study.

The Bradley Vehicle Study

The Bradley vehicle study was established to determine the optimal Inspect and Replace Only when Necessary (IRON) schedule. IRON is part of the Army's PDM program. The study established an optimal IRON schedule that minimized the life cycle cost of the weapon system. The Bradley vehicle study extracted data from 316 Bradley fighting vehicles during 16 Field Training Exercises (FTX) conducted at the National Training Center (NTC), Ft Erwin, CA. The vehicles were divided into classes by mileage. Each interval represented a multiple of 750 miles. The study focused on class averages:

> average man hours = sum man hours per class / sum miles per class
> average miles = sum miles per class / sum class observations

(Bradley: 1)

The Army constructed plots for maintenance cost vs. mileage and man-hours vs. mileage (where mileage is the average mileage per class). The maintenance cost and mileage relationship can be represented as:

$$y = ax^b$$

where

y = maintenance cost (average maintenance cost per class

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x = mileage (average miles per class)

a, b are constants

They further established the relationship between Man-hours and mileage as the linear model:

$$y = \beta_0 + \beta_1 x$$

where

y = man-hours (average man-hours per class)

x = mileage (average miles per class)

Both models were statistically significant. Utilizing the established relationship between maintenance cost and mileage, the optimal IRON cycle was 2 inspections for the lifetime of this weapon system. This is found by the difference in the cost curves over time (the difference is the savings) of no IRON's with one IRON, two IRON, and so forth. This assumes that an IRON inspection returns the vehicle to a "zero" mileage vehicle. The savings is optimized with two IRON inspections. This study, however, does not address the impact of the PDM inspection on weapon system availability.

Army Materiel Systems Analysis Activity Study

The Army Materiel Systems Analysis Activity (AMSAA) conducted a similar study, but AMSAA first wanted to validate the IRON program. If the IRON program significantly improved availability, then they would develop an IRON schedule that minimized life cycle cost. The study used M-1IP tanks during 19 FTX exercises at the NTC. Fourteen tanks entered Reliability Centered Inspect and Replace Only when Necessary (RC-IRON) maintenance and 46 non-RC-

IRON tanks participated in the exercise. The study found that the IRON program significantly reduced part replacements per mile, essential maintenance actions per mile, total maintenance actions per mile, man-hours, and support cost indicators. They did not, however, test for significance between the availability of the IRON and non-IRON tanks. The same methodology as the Bradley study was used to determine the optimal IRON schedule (Fox and Chung, 1991).

Aligning Demand for Spare Parts with their Underlying Failure Modes

A thesis by Kephart and Roberts attempted to predict the number of demands for aircraft reparables at the work unit code level. They used a three phase methodology which included a multiple linear regression, a Poisson regression, and lastly, fitting a Poisson process. The multiple regression model in their study used cumulative flying hours and number of sorties to predict the number of demands or maintenance actions of a work unit code.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_1^2 + \beta_4 x_2^2 + \beta_5 x_1 x_2$$

where

x_1 = commutative flying hours

x_2 = number of sorites

(Kephart and Roberts, 1995:3-9)

For the Poisson regression, Kephart and Roberts used three different link functions to predict the number of demands:

$$\mu(x, \beta) = \beta_0 + \beta_1 x_1$$

$$\mu(x, \beta) = \beta_0 + \beta_1 x_2$$

$$\mu(x, \beta) = \beta_0 + \beta_1 x_1 + \beta_2 x_2$$

(Kephart and Roberts, 1995:3-11)

The Poisson regression and the Poisson process analysis is detailed in Chapter 3. The results of the Kephart and Roberts study showed a limited relationship with demands and the independent variables. They attributed the inability to accurately model demands to the erratic nature of the demands (Kephart and Roberts, 1995:5-4). In other words, the failure rate was not stationary. They concluded that the "work unit code level demand/maintenance action estimates, which were based on flying hours and sorties from past demands, were poor estimators of future demands/maintenance actions" (Kephart and Roberts, 1995:5-4). The Poisson regression model will also be used in this study to model the failures per year of the LVS.

Bootstrap Technique

Similar to the Monte Carlo model suggested by Synergy, the bootstrap technique (described in The Introduction to the Bootstrap by Efron and Tibshirani) is a non-parametric technique that can model number of failures per year and downtime per year for a weapon system. This technique is describe in detail in Chapter 3. The bootstrap technique simulates a process which, in this case, is a failure process. The technique entails a random sampling with replacement from a process's empirical distribution to obtain the statistic of interest. The Kaplin-Meier technique described by Leemis in Reliability *Probabilistic Models and Statistical Methods* can be used to derive the empirical distributions for time to failure and service time. This technique is also described in more detail in Chapter 3.

Summary

Little research has been done to show the effect of PDM on overall weapon system availability, and the research that has been conducted has been limited to large, complex weapon

systems at the component level. Many weapon systems in the DoD inventory are not tracked at the component level, therefore, component level research can not be applied to all weapon systems. This research effort will be conducted in two phases. First, the failures per year will be modeled as a Poisson process using the Poisson regression, and secondly, the number of failures per year and downtime per year will be estimated using the bootstrap.

III. Methodology

The purpose of this study is to determine the loss of availability of a weapon system when, due to lack of funding, PDM could not be performed. If the PDM program reduces the number of failures per year per vehicle and reduces the downtime per failure, the increase in availability due to the PDM program can possibly be estimated. This chapter will outline the research questions, data collection, and proposed methodologies used to determine weapon system availability.

Research Questions

In order to determine the increase in availability of a weapon system due to PDM, the following questions must be answered:

1. Does PDM reduce the number of failures per year?
2. Does PDM reduce the amount of downtime once the weapon system has failed?

If PDM does reduce the number of failures per year and downtime per year, the increase in availability due to the PDM program can then be modeled and quantified.

Data Collection

Weapon system availability requires collection of failure data on a weapon system to be studied. More specifically, the weapon system's serial numbers, manufacturing dates, and failure data must be known for the entire inventory. This study will focus on the Marine Corps MK-48 or LVS. Unfortunately, the Marine Corps did not have a comprehensive list of their LVS inventory.

A partial list containing 1077 of the 1680 of the LVS's and their ship dates was obtained from Oshcosh, the manufacturer of the LVS. The serial numbers were assigned by Oshcosh in ascending order. The number of LVS's issued per year was obtained from the LVS item manager. The steps used to determine the valid serial numbers and there manufacturing dates were:

1. Generate a list of serial numbers from the Marine Corps' data base.
2. Remove serial numbers that were not the standard six digit numeric codes.
3. Compare the updated list with the list obtained from Oshcosh.
4. Remove invalid serial numbers from the first 1077 LVS serial numbers from updated list.
5. From the remaining serial numbers, count down and assign a manufacturing date to each vehicle.
6. Because the serial numbers are ascending, but are not sequential, try and identify correct serial numbers from those serial numbers that were removed.
7. Correct invalid serial numbers from data base (100 serial numbers were corrected).

The failure data were collected by the Marine Corps base's maintenance personnel. One data record was collected for each failure. The data collected for this research study included date the LVS was received, the date the LVS was released (date closed), echelon of maintenance, and mileage at the time of failure.

Unfortunately, this research study could not use mileage at the time of failure. More than one-third of the mileage data in the database were incorrect. The LVS has two usage meters, one to measure mileage and the other to measure hours of use. The Maintenance Directorate responsible for the LVS stated that either number could have been entered into the database and was unreliable. Many other mileage readings were either 0 or 999,999. Therefore, this part of the database was too corrupt to use in this research study.

The echelon of maintenance indicated the severity of the failure, as well as the type of maintenance performed on the vehicle. The manner in which it was recorded introduced another

problem in the data. Once an LVS failed, an entry was made in the database. If the shop could not fix the problem due to the severity of the failure, the LVS was transferred to another maintenance activity and another entry for the same failure was made into the database. Usually the previous entry was not closed out. Once the second maintenance activity fixed the failure, the second entry was closed, and the LVS was either sent back to the previous shop or directly released back into service. If the LVS was released directly into service, the second maintenance shop notified the first shop before it was released and the first entry was closed. If the LVS was sent back to the previous shop, the first entry was closed upon release. At first glance, these entries appear to be multiple failures, but in actuality, these entries only represent one failure with a downtime of latest date closed minus the earliest date received.

In order to analyze availability of the LVS that went to PDM, the serial number and dates received into PDM of the LVS's that went through programmed maintenance must be collected. The Marine Corps did not collect this information on the LVS. However, the item manager did keep a log of all vehicle serial numbers and the year and month of a PDM request. The time between the request and actual program maintenance was not known, but it is assumed to have a zero lag time. Mileage data and the amount of time a weapon system stayed in PDM were also not collected.

Maintenance data were collected from the first quarter of 1990 to the third quarter of 1995. This included 22,115 data entries. After the invalid serial numbers were removed, the file consisted of 20,830 data entries with 1567 valid serial numbers. Once the data entries were corrected to account for the LVS's being transferred from one maintenance activity to another, the data file consisted of 10,154 entries. A FORTRAN program was written to obtain the number of failures per year for each vehicle for the Poisson regression. A failure was counted as a no-

PDM failure if the vehicle did not go to PDM before the failure. A failure was counted as a PDM failure if the failure occurred after a vehicle went to PDM. When a failure occurred in a PDM year, this became a partial no-PDM year and a partial PDM year. An expected number of no-PDM failures and an expected number of PDM failures had to be calculated as if it was a full year. The expected number of no-PDM failures was equal to the number of failures before PDM divided by the fraction of the year the vehicle was in a no-PDM status. The expected number of PDM failures was equal to the number of failures after PDM divided by the fraction of the year the vehicle was in a PDM status.

Proposed Models

Two proposed methodologies will attempt to define the relationship between availability and PDM. First, a Poisson regression will attempt to quantify the relationship between PDM and the number of failures per year and predict the number of failures per year.

The second phase of this research study is non-parametric in nature. It involves the bootstrap technique described in The Introduction to the Bootstrap by Efron and Tibshirani. "The bootstrap technique is a database simulation developed to make certain statistical inferences" (Efron and Tibshiranti, 1993:1). This technique can be used to estimate sample means, standard deviations, confidence intervals, and so forth" (Efron and Tibshirani, 1993:vii). In general, the bootstrap technique will randomly draw samples with replacement from a population represented by empirical distributions. From this sample, a statistic of interest is then calculated. The experiment is replicated to define confidence intervals around the statistic of interest. This study will randomly draw a time to failure from its empirical distribution and a downtime from its empirical distribution repeating the process until the total number of days exceeds 365. This

procedure will be done for each vehicle in the fleet to obtain one bootstrap replication. The statistics of interest are the downtime per year per vehicle, number of failures per year per vehicle, and downtime the extending into the following year per vehicle. Confidence intervals will be calculated using 2000 bootstrap replications. The Kaplin-Meier technique will generate an empirical survival curve, S(t). The empirical distribution of the time to failure is then 1 - S(t).

Poisson Regression. Since the number of failures per year is a discrete response, this violates the normality assumption of the error terms for multiple linear regression. The number of failures, N(t), as a function of regressor variables, however, can be modeled assuming a Poisson process (Myers, 1986:333). The assumptions for a Poisson process are introduced in <u>Stochastic Processes</u> by Ross.

A stochastic process $\{N(t), t \geq 0\}$ is said to be a counting process, if $N(t)$ represents the total number of "events" that have occurred up to time t. Hence, a counting process $N(t)$ must satisfy:

(i) $N(t) \geq 0$
(ii) $N(t)$ is integer value
(iii) $s < t$, then $N(s) \leq N(t)$
(iv) For $s < t$, $N(t) - N(s)$ equals the number of events that have occurred in interval $(s,t]$

(Ross, 1983:31)

The counting process $\{N(t), t \geq 0\}$ is said to be a Poisson process having rate λ, $\lambda > 0$, if:

(i) $N(0) = 0$
(ii) The process has independent increments
(iii) The number of events in any intervals length t is Poisson distributed with mean λt. That is, for all s, $t \geq 0$,

$$P\{N(t+s) - N(s) = n\} = e^{-\lambda t} \frac{(\lambda t)^n}{n!}$$

where

$P\{N(t+s) - N(s) = n\}$ represents the probability on n failures in time interval t

(Ross, 1983:31)

Poisson regression assumes the number of failures per year does not change independently from one data point to the next but depends on a function of regressor variables, $\mu(x_i, \beta)$ $(i = 1, 2, \ldots, n)$, where n is the number of regressor variables. This function is often referred to as the link function and must always be non-negative (Myer, 1990:334). The proposed link function in this study is:

$$\mu(x, \beta) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6$$

where

$\mu(x, \beta)$ is the expected number of failures per year

$$x_1 = \begin{cases} 1, & \textit{if the LVS went to PDM} \\ 0, & \textit{otherwise} \end{cases}$$

$x_2 = \textit{years since last PDM}$

$$x_3 = \begin{cases} 1, & \textit{if the LVS was manufactured in 85} \\ 0, & \textit{otherwise} \end{cases}$$

$$x_4 = \begin{cases} 1, & \textit{if the LVS was manufactured in 86} \\ 0, & \textit{otherwise} \end{cases}$$

$$x_5 = \begin{cases} 1, & \textit{if the LVS was manufactured in 87} \\ 0, & \textit{otherwise} \end{cases}$$

$$x_6 = \begin{cases} 1, & \textit{if the LVS was manufactured in 88} \\ 0, & \textit{otherwise} \end{cases}$$

If the LVS was manufactured in 89, $x_i = 0$, $i = 3 \ldots 6$.

The Poisson regression model assumes a stationary failure rate. In order to test this assumption, a separate Poisson regression will attempt to show the year of the failure is not significant. The proposed link function for this Poisson regression is:

$$\mu(x,\beta) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6 + \beta_7 x_7 + \beta_8 x_8 + \beta_9 x_9$$

where

$\mu(x,\beta)$ is the expected number of failures per year

$$x_1 = \begin{cases} 1, & \textit{if the LVS went to PDM} \\ 0, & \textit{otherwise} \end{cases}$$

$$x_2 = \begin{cases} 1, & \textit{if the LVS was manufactured in 85} \\ 0, & \textit{otherwise} \end{cases}$$

$$x_3 = \begin{cases} 1, & \textit{if the LVS was manufactured in 86} \\ 0, & \textit{otherwise} \end{cases}$$

$$x_4 = \begin{cases} 1, & \textit{if the LVS was manufactured in 87} \\ 0, & \textit{otherwise} \end{cases}$$

$$x_5 = \begin{cases} 1, & \textit{if the LVS was manufactured in 88} \\ 0, & \textit{otherwise} \end{cases}$$

$$x_6 = \begin{cases} 1, & \textit{if the failure occured in 1991} \\ 0, & \textit{otherwise} \end{cases}$$

$$x_7 = \begin{cases} 1, & \textit{if the failure occured in 1992} \\ 0, & \textit{otherwise} \end{cases}$$

$$x_8 = \begin{cases} 1, & \textit{if the failure occured in 1993} \\ 0, & \textit{otherwise} \end{cases}$$

$$x_9 = \begin{cases} 1, & \textit{if the failure occured in 1994} \\ 0, & \textit{otherwise} \end{cases}$$

If the LVS was manufactured in 89, $x_i = 0$, $i = 2 \ldots 5$.

If the failure occurred in 1995, $x_i = 0$, $i = 6 \ldots 9$.

To ensure that the number of failures per year per vehicle follow a Poisson distribution, the number of failures per year per group will be subjected to a Chi-Squared goodness of fit test.

The test statistic for the Chi-Squared test is:

$$\sum_{j=1}^{k} \frac{\left(N_j - np_j\right)^2}{np_j} \, .$$

where

    k is the number of intervals

    N_j is the number of x_i's in the jth interval $[a_{j-1}, a_j)$

    p_j is $\displaystyle\sum_{a_{j-1} \leq x_i \leq a_j} \hat{p}(x_i)$

    $\hat{p}(x_i)$ is the probability density function of the Poisson distribution
                                                     (Law and Kelton, 1991:382)

The hypothesis test for goodness of fit is for the Poisson distribution is:

H_o: number of failures per year is Poisson
H_a: not Poisson

We reject H_o if the test statistic is greater than $\chi^2_{k-m-1,1-\alpha}$

where

    m is the number of parameters to be estimated

    $\alpha = .05$
                                                     (Law and Kelton, 1991:383)

If H_o is not rejected, the failure data for the LVS can be assumed to follow a Poisson distribution. This supports the use of a Poisson regression model on the LVS failure data.

YEARS SINCE PDM indicates the years since an LVS's manufacturing date or since PDM. Since there can be multiple failures in a given year, the years since PDM variable had to be aggregated into one value. The failures are assumed to occur uniformly throughout the year and the mid-point of that year (182.5 days) was used to calculate the years since PDM. If a failure occurred in a PDM year, the years since PDM was calculated as the proportion of the year in PDM status. To ensure that the failures in a given year occur uniformly throughout the year, the failures will be subjected to a Chi-Squared goodness of fit test. The hypothesis test for goodness of fit for the uniform is:

H_o: failures are uniformly distributed through out the year
H_a: not uniform

We reject H_o if the test statistic is greater than $\chi^2_{k-m-1,1-\alpha}$

where

m is the number of parameters to be estimated

$\alpha=.05$

(Law and Kelton, 1991:383)

If H_o is not rejected, failures for the LVS can be assumed to occur uniformly throughout the year. This also suggests that the expected day in which a failure occurs will be on the 182.5 day of the year. For the variable YEARS SINCE PDM, the days in which failures occur can be aggregated into one time of failure occurring on the 182.5 day of the year.

Since this model uses a link function to predict the number of failures, the model for the a Poisson process with regressor variables is:

$$P(y_i;\beta) = e^{-t_i[\mu(\boldsymbol{x}_i,\beta)]} \frac{[t_i\mu(\boldsymbol{x}_i,\beta)]^{y_i}}{y_i!}$$

where

$P(y_i;\beta)$ represents the probability of y_i failures occurring
at by time t_i

$\mu(\boldsymbol{x}_i,\beta)$ represents the Poisson mean which replaces μ in
the standard Poisson process

β represents a vector of parameters to be estimated

$\boldsymbol{x}_i$ represents a regressor variable

t_i represents time

y_i represents the number of failures

(Myer, 1990:334)

The model for the Poisson mean is:

$$\mu_i = t_i\mu(\boldsymbol{x}_i,\beta)$$

where

$i = 1, 2, \ldots, n$

(Myer, 1990:334)

In this study, t_i will always equal one because the proposed Poisson regression is modeling

failures per year.

The Poisson regression estimates β by maximizing the likelihood function. The likelihood

function for the Poisson regression is:

$$L(y,\beta) = \prod_{i=1}^{n} p(y_i,\beta)$$

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$$L(\mathbf{y}, \beta) = \prod_{i=1}^{n} e^{-t_i[\mu(\mathbf{x}_i, \beta)]} \frac{[t_i \mu(\mathbf{x}_i, \beta)]^{y_i}}{y_i!}$$

<div align="right">(Myer, 1990:334)</div>

The procedure used to find the maximum likelihood estimators for Poisson regression is iteratively reweighted least squares (Myer, 1990:335). The likelihood equations to be solved for the Poisson regression are:

$$\frac{\partial \ln L(\mathbf{y}, \beta)}{\partial \beta} = 0$$

or,

$$\sum_{i=1}^{n} \left[\frac{y_i}{\mu(\mathbf{x}_i, \hat{\beta})} - t_i \right] \left[\frac{\partial \mu(\mathbf{x}_i, \hat{\beta})}{\partial \hat{\beta}} \right] = 0$$

<div align="right">(Myer, 1990:334)</div>

Siegel notes that this model relates the link function to the natural logarithm of the number of failures per year (Siegel, 1992:180).

The measure for lack of fit uses a statistic called the deviance (McCullagh and Nelder,1992:197). Deviance is defined as:

$$D(\mathbf{y}, \mu) = 2 \cdot \sum \left\{ y_i \log\left(\frac{y_i}{\mu_i}\right) - (y_i - \mu_i) \right\}$$

<div align="right">(McCullagh and Nelder, 1992:197)</div>

The deviance is approximately distributed as a χ^2 distribution with n-k-1 degrees of freedom where n is the sample size and k is the number of parameters to be estimated plus one. The hypothesis test to measure the lack of fit is:

H_o: model is Poisson
H_a: not Poisson

We reject H_o if $D(\mathbf{y}, \mu)$ is greater than $\chi^2_{n-k-1, 1-\alpha}$
where

$$\alpha = .05$$

(Myer, 1990:324)

If H_o is not rejected, than the model can be assumed to be Poisson. This will provide statistical significance to the results of the tests on the individual coefficients.

The individual coefficients can be tested similarly to a t-test in multiple linear regression, but they also follow a χ^2 distribution with one degree of freedom. The test statistic is :

$$\frac{b_i}{c_i}$$

where

$i = 0, 1, \ldots k\text{-}1$

b_i = the parameter estimate for β_i

c_i = the standard error

The hypothesis test for the individual coefficients is:

H_o: $\beta_i = 0$
H_a: $\beta_i \neq 0$ given the rest of the coefficients are in the model

We reject H_o if $\dfrac{b_i}{c_i}$ is greater than $\chi^2_{\alpha,1}$

where

$$\alpha = .05$$

(Siegel, 1992:181)

If H_o is rejected, the coefficients can be assumed to be significantly different than zero, and it can be assumed that the variable corresponding to the coefficients contributes to the number of failures per year.

An F-test will test if the failure rate for PDM vehicles is significantly different than the failure rates for no-PDM vehicles. The test statistic for the F-test is:

$$\frac{\hat{\lambda}_1}{\hat{\lambda}_2}$$

where

$$\hat{\lambda}_1 > \hat{\lambda}_2$$

The hypothesis test the difference of two failure rates is:

H_o: $\lambda_1 = \lambda_2$
H_a: $\lambda_1 \neq \lambda_2$

We reject H_o if $\dfrac{\hat{\lambda}_1}{\hat{\lambda}_2}$ is greater than $F_{2r_1, 2r_2, 1-\frac{\alpha}{2}}$

where

$$\alpha = .05$$

(Leemis, 1995:210)

If H_o is rejected, the failure rates for PDM and no-PDM can be assumed to be statistically different. This also suggests that the failure rates for PDM are significantly lower than no-PDM failure rates.

Bootstrap Technique. "The bootstrap method is a computer-based method for assigning measures of accuracy to statistical estimates" (Efron and Tibshirani, 1993:10). In this study, the statistical estimate will be downtime per vehicle per year. Vehicles will be differentiated by their PDM status and manufacturing year. The process involves independently sampling with replacement from two empirical probability distributions: $\hat{F}$ (status, year group) to obtain bootstrap samples x^* for time to failure and $\hat{G}$ (status, year group) to obtain bootstrap samples y^* for downtime after failure. The Probability Distributions, $\hat{F}$ (status, year group) and $\hat{G}$ (status, year group), will be 1-S(t), where S(t) is the survivor functions estimated using the Kaplin-Meier technique which will be addressed later in this section. The sampling will end when the total days

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exceed 365 days. This will be repeated k times where k is the number of trucks in the simulation. In this study, k is 1000 trucks. The statistics of interest are the average downtime per vehicle, average number of failures per vehicle, and average downtime in the following year per vehicle for a single year. Each statistic of interest is considered one bootstrap sample and is defined as:

$$S(x^{*b}) = \frac{\sum_{i=1}^{k} downtime}{k}$$

$$S(x^{*b}) = \frac{\sum_{i=1}^{k} number\ of\ failures}{k}$$

$$S(x^{*b}) = \frac{\sum_{i=1}^{k} downtime\ in\ the\ next\ year}{k}$$

where

b is the index for the bth bootstrap sample

(Efron and Tibshirani, 1993:47)

The number of replications of the bootstrap sample should be chosen to minimize the standard error. Unfortunately, for most statistics there is no limiting value of the standard error (Efron and Tibshirani, 1993:15). Efron and Tibshirani state that there seldom are more than 200 replications needed, but more replications are required for bootstrap confidence intervals (Efron and Tibshirani, 1993:53). More specifically, the number of replications increases by a factor of ten for a confidence interval (Efron and Tibshirani, 1993:15). Thus, the number of replications in this study, B, is 2000.

The bootstrap statistic is defined as:

$$S(x^*) = \frac{\sum_{i=1}^{B} S(x^{*b})}{B}$$

(Efron and Tibshirani, 1993:47)

This bootstrap statistic represents the steady state values obtained from bootstrap sample.

The standard error is defined as:

$$s\hat{e}_{boot} = \left\{ \sum_{b=1}^{B} \left[\frac{\left[S(x^{*b}) - S(\circ) \right]^2}{B-1} \right] \right\}^{\frac{1}{2}}$$

where

$$S(\circ) \text{ is } \frac{\sum_{b=1}^{B} S(x^{*b})}{B}$$

(Efron and Tibshirani, 1993:47)

The 90% confidence interval is defined as:

$$S(x^*) \pm 1.645(s\hat{e}_{boot})$$

(Efron and Tibshirani, 1993:153)

Kaplan-Meier Survival Curve. The typical non-parametric estimation of a survivor curve is:

$$\hat{S}(t) = \frac{N(t)}{n}, t \geq 0$$

where

$N(t)$ is the number of failures at time t

n is total number of failure times

(Leemis, 1995:254)

This estimation will be used to estimate the empirical downtime distributions. The step function has a downward step of $1/n$, and all n values have equal step mass. Ties are easily corrected by changing the step size to d/n where d is the number of ties. This method does not take into account right-censored data, indicating vehicles which did not fail before the study concluded. The Kaplan-Meier offers a non-parametric technique which handles right-censored data. The Kaplan-Meier technique is defined as:

$$\hat{S}(t) = \prod_{j \in R(t)'} \left[1 - \frac{d_j}{n_j} \right]$$

where

d_j denotes the number of observed failures at time y_j; $j=1, 2, .. k$

k denotes the number of failure times

y_j denotes the jth failure time

n_j denotes the number of items on test just before time y_j (This includes any values that are cencored at time y_j)

$R(t)'$ denotes the set of all indexes of items that are at risk just before time $y_j = t$

(Leemis, 1995:256)

The Fleming and Harrington log-rank test and the Peto-Peto modification of the Fleming and Harrinton log-rank test compare the survivor functions of two different groups (Venables and Ripley, 1994: 273). Suppose i groups, with n_i survival times, have d observed deaths at time t_j (where j is the number of unique death times from the i groups). The test statistic for the log-rank test is:

$$(\mathbf{O} - \mathbf{E})^T \mathbf{w} \mathbf{V}^{-1} (\mathbf{O} - \mathbf{E})$$

where

wV is the weighted covariance matrix of (**O** - **E**)

w is one for the log-rank test

w is the Kaplan-Meier product limit estimator for the Peto-Peto modification

(Venables and Ripley, 1994: 273)

The test statistic is distributed as a $\chi^2_{\alpha,i-1}$. The hypothesis test is:

H_o: the two survivor curves are the same
H_a: the two survivor curves are not the same

We reject H_o if log-rank test statistic is greater than $\chi^2_{\alpha,i-1}$

where
$\alpha=.05$

If H_o is rejected for all the survivor curves, the PDM and no-PDM survivor curves are statistically different. This further suggests that the PDM vehicles remain in service longer between failures and no-PDM vehicles remain in the maintenance facility longer after failure.

The techniques described in this chapter will be implemented on the LVS data to attempt to estimate the availability of the PDM and non-PDM vehicles.

IV. Results and Analysis

This chapter will outline the results from the methodologies introduced in Chapter 3. The first section will detail the results of the Poisson regression, beginning with a discussion of the assumptions. Next, the results of the Poisson distribution goodness of fit for the number of failures per year and the results of the uniform distribution goodness of fit for the failures occurring within each year will be presented. The results of the Poisson regression will then be presented with a detailed analysis of the residuals. The second section will detail the results of the bootstrap technique. First, the Kaplan-Meier results will be presented and finally the results of the bootstrap will be discussed with its implications.

Poisson Regression

To assume the number of failures per year per group is a Poisson process, the number of failures per year must be Poisson distributed. To test this assumption, a Chi-Squared Goodness of Fit test was conducted using Best Fit. The results of the test are given in Table 1. The graphs depicting the number of failures per year and their parametric Poisson distribution are included in Appendix A.

The number of failures per year for all the groups represented in Table 1, with the exception of the year 1989 no-PDM group, fail to reject the null hypothesis and may be assumed to follow a Poisson distribution. It is not surprising that the year 1989 no-PDM group rejected the null hypothesis. The 1989 year group has a small sample size, only 31 vehicles for 1989, and these vehicles are relatively new compared to the other vehicles. In general, the 1989 year vehicles

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Table 1

χ^2 Goodness of Fit Results for the Poisson Distribution

GROUP	χ^2	P-VALUE	HYPOTHESIS TEST	RESULT $\alpha = .05$
85 no-PDM	5.51	0.788	H_o: POISSON H_a: NOT POISSON	DO NOT REJECT H_o
85 PDM	7.19	0.617	H_o: POISSON H_a: NOT POISSON	DO NOT REJECT H_o
86 no-PDM	11.22	0.261	H_o: POISSON H_a: NOT POISSON	DO NOT REJECT H_o
86 PDM	4.44	0.88	H_o: POISSON H_a: NOT POISSON	DO NOT REJECT H_o
87 no-PDM	7.18	0.618	H_o: POISSON H_a: NOT POISSON	DO NOT REJECT H_o
87 PDM	3.4	0.946	H_o: POISSON H_a: NOT POISSON	DO NOT REJECT H_o
88 no-PDM	0.37	0.999	H_o: POISSON H_a: NOT POISSON	DO NOT REJECT H_o
88 PDM	15.64	0.075	H_o: POISSON H_a: NOT POISSON	DO NOT REJECT H_o
89 no-PDM	67.93	0	H_o: POISSON H_a: NOT POISSON	REJECT H_o

did not fail often, but there is an "outlier" vehicle with10 failures. Of the other groups in Table 1, the 1988 PDM group has a relatively low P-value. (The P-value represents the probability of obtaining the data given the underlying distribution is a Chi-Squared distribution.) With the exception of the 1989 no-PDM vehicles, the failures per year per group may be assumed to be Poisson distributed.

The Poisson process assumes that the failures per year are independent. However, the type of failure that occurs influences the number of failures per year. If a vehicle experiences a major failure, the vehicle will be down for a significant period of time; this vehicle will not be at risk during the downtime and may experience fewer failures per year. The failures per year, as

shown by the service time survivor curves in the bootstrap technique section in this chapter, are not independent because the service times for the LVS are large. Therefore, vehicles that experience a failure at the end of the year are potentially not at risk for failure a large portion of time the following year. The violation of the independence assumption will increase the variability of the number of failures per year an LVS experiences.

The data set is incomplete for the year 1995. The data set obtained from the Marine Corps includes failures from January 1990 to September 1995. The data did not include any failures that occurred after the 272 day of 1995 or any vehicles that were not repaired before that date. Since this can lead to bias, (failures occur in 1994 or 1995 but are not represented in the data set because they are not repaired by September 1995) the failures occurring in 1995 have been omitted from this part of the study.

The Poisson process also assumes a constant, or stationary, failure rate for each class of vehicles. The number of failures per year is relatively constant (1620 failures in 1990, 1547 failures in 1991, 1652 failures in 1992, 1472 failures in 1993, 1732 failures in 1994, and 1838 failures in 1995), but the number of failures does decrease in 1993 and starts to increase in 1994 and 1995.

One possible interpretation of the increase in the number of failures per year in 1994 and 1995 is the existence of a bathtub-shaped hazard function. The hazard function is defined as the "ratio of the probability density function to the survivor function" (Leemis, 1995:49). "The importance of the hazard function is that it indicates the change in the failure rate over the life of a population of devices" (Kapur and Lamberson, 1977:12). A bathtub-shaped hazard function assumes a system experiences an initial decrease in the hazard function, but then increases with age (Leemis, 1995:51). First, in the infancy stage, the hazard rate decreases with time. This is

often called the "burn in" period (Leemis, 1995:51). Once the system survives past this initial period, the system has a fairly constant hazard function (Leemis, 1995:51). However, as the system continues to age, the hazard function starts to increase and these failures are known as "wear-out" failures (Leemis, 1995:51). The increase in the number of failures in 1994 and 1995 may be attributed to an increase in the hazard function of the LVS, and thus failures be considered "wear-out" failures.

The increasing failure rate is not surprising because the vehicles are getting older, and vehicle failure rates tend to increase with time. Added to this, the 85 year vehicles are almost 10 years old in 1995 and will be scheduled for their mid-life PDM in 1996 (Joe Littleton, 1996).

The failure rates, shown in Table 5, show the failures per year for no-PDM vehicles is approximately 1.2 failures per year and for PDM vehicles is approximately .33 failures per year. The scatter plot of the number of failures per year per group is included in Appendix B. This graph shows the extensive variability of the number of failures per year experienced by the LVS for both no-PDM and PDM vehicles. Since this model explicitly assumes a constant failure rate, a Poisson regression is used to determine if the year of the failure is significant variables. Table 2 shows the results of Poisson regression with only classification variables.

Note the year in Table 2 represents the failures that occur in the previous year. The Poisson regression results are inconclusive because the test for goodness of fit rejects the null hypothesis that the model is Poisson. The link function for this model does not capture the variability of the number of failures per year, thus the model can not be assumed to be Poisson. No degree of confidence can be obtained from the P-values for the coefficients; however, there is evidence that suggests failures in 1993 are significant. The total number of failures decrease in

Table 2

Poisson Regression Results with only Classification Variables

PREDICTOR VARIABLES	COEFICIENTS	STD ERROR	COEFFICIENT STD ERROR	P VALUE	HYPOTHESIS TEST	RESULT $\alpha = .05$
CONSTANT	-2.00726	0.28888	-6.95	0	H_o: $\beta_0 = 0$ H_a: $\beta_0 \neq 0$	Reject H_o
PDM	-1.22633	0.07128	-17.2	0	H_o: $\beta_1 = 0$ H_a: $\beta_1 \neq 0$	Reject H_o
Y85	2.09137	0.29067	7.19	0	H_o: $\beta_2 = 0$ H_a: $\beta_2 \neq 0$	Reject H_o
Y86	1.99975	0.28885	6.92	0	H_o: $\beta_3 = 0$ H_a: $\beta_3 \neq 0$	Reject H_o
Y87	2.22741	0.28873	7.71	0	H_o: $\beta_4 = 0$ H_a: $\beta_4 \neq 0$	Reject H_o
Y88	2.15801	0.28869	7.48	0	H_o: $\beta_5 = 0$ H_a: $\beta_5 \neq 0$	Reject H_o
Y91	-0.06069	0.03585	-1.69	0.9448	H_o: $\beta_6 = 0$ H_a: $\beta_6 \neq 0$	Do Not Reject H_o
Y92	-0.11651	0.03626	-3.21	0.2627	H_o: $\beta_7 = 0$ H_a: $\beta_7 \neq 0$	Do Not Reject H_o
Y93	-0.04103	0.03572	-1.15	0.9134	H_o: $\beta_8 = 0$ H_a: $\beta_8 \neq 0$	Do Not Reject H_o
Y94	-0.09445	0.03654	-2.58	0.0241	H_o: $\beta_9 = 0$ H_a: $\beta_9 \neq 0$	Reject H_o

DEVIANCE   9563.69
P-VALUE   0
DEGREES OF FREEDOM   783 2

1993, but the number of failures increase in 1994 and 1995. The significance of the 1993 failures and the increase in the 1994 and 1995 failures implies a non-stationary process. This deviation from the non-stationary assumption will ultimately effect the point estimates of the coefficients for the independent variables and the confidence of the P-values for the independent variables.

In order to use the variable YEARS SINCE LAST PDM, the failures in a given year must occur uniformly throughout the year. The results of the Chi-Squared goodness of fit test, using Microsoft Excel, for the failures occurring uniformly throughout the year are included in Table 3. The graphs, depicting the number of failures in a year separated into 20 equal intervals, are

Table 3

χ^2 Goodness of Fit Results for the Uniform Distribution

YEAR	AVERAGE	χ^2	P-VALUE	HYPOTHESIS TEST	RESULT $\alpha = .05$
90	176.43	86.86	P-= 0.00	H_0: UNIFORM H_a: NOT UNIFORM	REJECT H_0
91	175.03	227.13	P-= 0.00	H_0: UNIFORM H_a: NOT UNIFORM	REJECT H_0
92	181.86	135.53	P-= 0.00	H_0: UNIFORM H_a: NOT UNIFORM	REJECT H_0
93	167.09	95.59	P-= 0.00	H_0: UNIFORM H_a: NOT UNIFORM	REJECT H_0
94	180.49	85.11	P-= 0.00	H_0: UNIFORM H_a: NOT UNIFORM	REJECT H_0
95	159.78	986.98	P-= 0.00	H_0: UNIFORM H_a: NOT UNIFORM	REJECT H_0

included in Appendix C. None of the years have failures that are uniformly distributed, and they all reject the null hypothesis that their underlying distributions are uniform. However, since the average day that failures occur is close to the midpoint of the year for every year, this study uses an expected day of failure of 182.5.

Since the number of failures per year per group can be assumed to be Poisson distributed and the failures occur near the midpoint of the year, a Poisson regression is used to attempt to predict the number of failures per year. The Poisson regression results using Statistix 4.1 are included in Table 4. The hypothesis test, that the model is Poisson, is rejected resulting in the conclusion that the model is not Poisson. The results in Appendix A, however, conclude the failures per year per group are Poisson. The rejection of the null hypothesis suggests the proposed link function for the Poisson regression does not model the underlying Poisson process. This, however, does not suggest that the failure process for each group does not follow a Poisson

Table 4

Results of the Poisson Regression with the Number of Failures per Year

PREDICTOR VARIABLES	COEFICIENTS	STD ERROR	COEFFICIENT STD ERROR	P - VALUE	HYPOTHESIS TEST	RESULT $\alpha = .05$
CONSTANT	-2.11325	0.28869	-7.32	0.0000	H_o: $\beta_o = 0$ H_a: $\beta_o \neq 0$	Reject H_o
PDM	-1.16268	0.07494	-15.52	0.0000	H_o: $\beta_1 = 0$ H_a: $\beta_1 \neq 0$	Reject H_o
Y85	2.02281	0.29222	6.92	0.0000	H_o: $\beta_2 = 0$ H_a: $\beta_2 \neq 0$	Reject H_o
Y86	1.94813	0.28970	6.72	0.0000	H_o: $\beta_3 = 0$ H_a: $\beta_3 \neq 0$	Reject H_o
Y87	2.19211	0.28912	7.58	0.0000	H_o: $\beta_4 = 0$ H_a: $\beta_4 \neq 0$	Reject H_o
Y88	2.14012	0.28876	7.41	0.0000	H_o: $\beta_5 = 0$ H_a: $\beta_5 \neq 0$	Reject H_o
YRAFTPDM	0.01760	0.00805	2.19	0.0288	H_o: $\beta_6 = 0$ H_a: $\beta_6 \neq 0$	Reject H_o

DEVIANCE   9571.52
P-VALUE   0

process. This contradiction is explained by the variability of the number of failures per year not explained by the model perhaps due to the inability of the independent variables to capture any substantial increase in the number of failures per year. All the variables are statistically significant, but since the model is not Poisson, a statistical confidence of the variable coefficients can not be determined. The P-values for the variable coefficients are only valid if the model is significant.

Unlike linear regression, the magnitude of the effect of the variables on the number of failures per year can not directly be obtained from Table 4. The fitted values of the Poisson regression model are obtained using the function: $e^{\mu(x, \beta)}$ (Siegel, 1992:180). The expected number of failures for a no-PDM year 85 vehicle that has been in service for ten years is 1.089

failures. The expected number of failures for a PDM year 85 vehicle that has been in service for five years after PDM is .3119 failure. The other year group vehicles of the same PDM status display similar expected number of failures per year. This suggests that the PDM *is* an effective program that does decrease the expected number of failures per year.

This model either overestimates the failures per year or grossly underestimates the failures per year. Appendix D includes the scatter plot of the residuals and the actual number of failures per year and the Wilk-Shapiro Rankit Plot for normality of the residuals. The residual plot in Appendix D shows two distinct groups: The higher error is the PDM group while the lower is the no-PDM group.

This model does not capture the variability of PDM failures per year or the no-PDM failures per year. The model predicts only a fraction of a failure for the PDM vehicles and approximately one failure for no-PDM vehicles. If a vehicle does not fail in a year, it has a slightly negative residual for the PDM vehicles and a residual of approximately one for no-PDM vehicles. However, if the vehicle exhibits multiple failures, there is a significantly higher residual. This is clearly seen in the residual plots with the fitted values. Appendix E includes the residual plots for the independent variables and the fitted variables. Figure 1 shows the a plot of the number of failures per year by year. Figure 1, like Appendix B, shows the variability of the failures per year for the LVS. Appendix D shows an increasing error rate for the Poisson regression model as the number of actual failures increase. This is explained by the Poisson regression's expected number of failures per year for all the groups being less than 1.3 failures per year.

The residual plot for the YEARS SINCE LAST PDM in Appendix E shows that this variable has little explanatory power. The residuals show no distinct pattern. With the lack of a

Scatter Plot of NUMFAIL vs YEAR
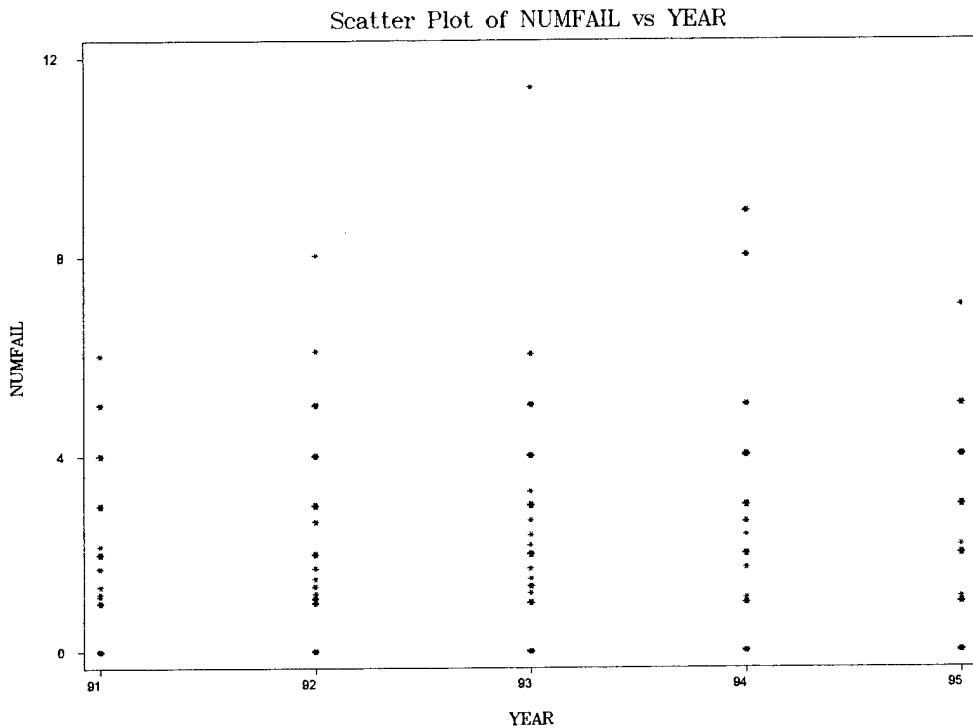
Figure 1 Plot of the Failures per Year by Year

significant variable that captures usage, the increase in the amount of failures can not be explained

in this model.

The Wilk-Shapiro Rankit plot in Appendix D shows that the error terms are not normally

distributed. The error terms for the Poisson regression model are assumed to be normally

distributed, but in this case are not because the large variability in the number of failures per year

that is not captured by this model.. Nelder and McCullagh offer a variance stabilizing transform

for the Poisson distribution:

$$E(Y^{1/2}) \approx \mu^{1/2}$$
$$VAR(^{1/2}) \approx \frac{1}{4}$$

(Nelder and McCullagh, 1992:196)

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However, this transformation only applies to large values of μ (Nelder and McCullagh, 1992:196). This transformation can not be used in this case because the expected number of failures for a PDM vehicle is less than one. There is evidence that the PDM program does reduce failures, but Poisson regression provides no level of statistical confidence for the independent variable point estimates because the data do not support the model assumptions.

To test whether the failures per year are significantly different for PDM and no-PDM vehicles, an F-test was performed on each year group's failure rates. Table 5 shows the results of the tests.

Table 5

F-test for the Difference in Failure Rates for PDM and no-PDM Vehicles

CLASS	NUMBER OF FAILURES	$\hat{\lambda}$	STD DEV	$\hat{\lambda}_I$	HYPOTHESIS TEST	$\dfrac{\hat{\lambda}_1}{\hat{\lambda}_2}$	P VALUE	RESULT
85 no-PDM	617.04	1.0115	1.1605	$\hat{\lambda}1$	H_o: $\lambda_1 = \lambda_2$			
85 PDM	34.575	0.3602	0.754	$\hat{\lambda}2$	H_a: $\lambda_1 \neq \lambda_2$	2.8081	P=0	REJECT H_o
86 no-PDM	2014.4	0.9334	1.1635	$\hat{\lambda}1$	H_o: $\lambda_1 = \lambda_2$			
86 PDM	83.441	0.2616	0.6606	$\hat{\lambda}2$	H_a: $\lambda_1 \neq \lambda_2$	3.5680	P=0	REJECT H_o
87 no-PDM	2343.1	1.1716	1.0785	$\hat{\lambda}1$	H_o: $\lambda_1 = \lambda_2$			
87 PDM	59.509	0.3343	0.7415	$\hat{\lambda}2$	H_a: $\lambda_1 \neq \lambda_2$	3.5046	P=0	REJECT H_o
88 no-PDM	2512.6	1.092	1.0883	$\hat{\lambda}1$	H_o: $\lambda_1 = \lambda_2$			
88 PDM	27.944	0.3408	0.8463	$\hat{\lambda}2$	H_a: $\lambda_1 \neq \lambda_2$	3.2042	P=0	REJECT H_o
89 no-PDM	12	0.1263	0.334					

Table 5 shows the failure rates for no-PDM vehicles are approximately one failure per year, and the failure rates for PDM vehicles are approximately one third failure per year. This is approximately the same results of the Poisson regression. The hypothesis tests reject H_o, which implies the failure rates for PDM and no-PDM *are* significantly different, and PDM significantly reduces the number of failures per year.

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Boot Strap Technique

Bootstrap estimates for number of failures per year and downtime per year are not obtained for the 1989 year group vehicles because of the relatively small sample size. The bootstrap technique uses all the times to failure and the service time distributions from all the years in the data set. It has been shown that the failure rates are increasing in 1994 and 1995. Thus, when the bootstrap samples from the empirical time to failure distribution prior to 1993, the expected time to failure will be larger than the current (1995) time to failure. This potentially results in a decrease in the number of failures per year. This will bring bias to the bootstrap result, but the ultimate result will be a more conservative estimate.

The results of the hypothesis testing on the Kaplan-Meier estimation of the survivor curves for PDM and no-PDM using S-plus are included in Appendix F. For all the year groups, the failure curves for PDM and no-PDM are significantly different. This suggests the PDM vehicles survive longer without failure. The service time curves for PDM and no-PDM, with the exception of the 1988 year group, are significantly different. This suggests that the PDM vehicles (except the 1988 year group) are not out of service as long as no-PDM vehicles. The plots for the survivor curves are included in Appendix G. The results of the bootstrap technique are included in Table 6, the 95 percent confidence intervals are included in Appendix H and graphs of the bootstrap results are included in Appendix I. While the number of failures per year developed from the Poisson regression could not pass the rigors of a statistical test, they are not drastically different from the significant values obtained using the bootstrap technique.

The bootstrap estimates of downtime for no-PDM and PDM are distinctly different. The no-PDM group is out of service 3 to 4 times as long as the PDM group. The significant amount

Table 6

Bootstrap Technique Results

GROUP	DOWN TIME	STD DEV	NUM FAIL	STD DEV	DOWNTIME NEXT YEAR	STD DEV
85 NO PDM	119.601665	3.4900039	1.1495375	0.027741	56.3517945	3.245101
85 PDM	41.186188	2.4101167	0.561372	0.023662	13.694968	1.569306
86 NO PDM	115.434678	3.5569385	1.1736125	0.02941	59.1211875	3.508131
86 PDM	18.1646545	1.7518671	0.3586975	0.020442	4.075965	0.934783
87 NO PDM	135.033182	3.9347049	1.430694	0.02987	70.3846965	3.578988
87 PDM	52.8839895	2.8621704	0.619728	0.026985	13.964259	1.736707
88 NO PDM	112.994979	3.3361717	1.333514	0.032129	52.6088685	3.25806
88 PDM	32.161272	2.4872614	0.351101	0.019485	18.2325805	2.154502

of time the LVS stays out of service supports the conclusion that the number of failures per year is not independent from year to year because if a failure occurs near the end of a year, the vehicle will not be at risk to fail a large portion of the following year. When the no-PDM vehicles are out of service for approximately one third of the year, they are not at risk to fail as often as PDM vehicles. The no-PDM vehicles fail more than twice as often, while the PDM vehicles are at risk of failure approximately 90 days a year longer than the no-PDM vehicles.

The results of this research suggests the number of failures per year is approximately one failure per year for no-PDM vehicles and is approximately one third of a failure per year for PDM vehicles, and the no-PDM vehicles are unserviceable for a significant period of time after failure. This has many possible implications: the vehicles can be experiencing major failures, and the vehicle is essentially rebuilt at base level, or the supply system could have difficulty re-supplying the maintenance facilities with the needed repair parts. Of course, there may be other factors beyond the reach of this analysis. Research does imply, however, that there is a significant decrease in the number of failures per year and the downtime per year for PDM vehicles.

The results of the Poisson regression reveal that there may be a difference in the number of failures per year for PDM and no-PDM vehicles, but a statistical confidence of the coefficients can not be obtained because of the lack of model significance. However, the expected number of failures per year for each group is approximately the same as those obtained from the bootstrap estimation. The 1994 and 1995 failure data indicate that the failure rates for the LVS vehicles are increasing. Therefore, the bootstrap results represent a conservative estimate, and the availability of the LVS in the future may be worse.

The bootstrap estimates show that the LVS is out of service approximately 33 percent of the time for no-PDM vehicles. However, sending the vehicles to PDM will decrease this out service rate to approximately 10 percent. This study also reveals a significant problem bringing a broken no-PDM LVS back into service. While theoretical statistical questions remain due to the data limitations, PDM appears to significantly reduce the number of failures per year. The amount of time an LVS remains in the maintenance facility is a major factor for the decreased availability of the LVS, particularly for no-PDM vehicles.

V. Conclusions and Recommendations

The purpose of this chapter is to present the conclusions and recommendations obtained in this research study. Initially, the research questions will be addressed; then the limitations of the study will be presented. Finally, the results and implications will be discussed followed by recommendations for further study.

Research Questions

The research questions answered in this study are:

1. Does PDM reduce the number of failures per year?
2. Does PDM reduce the amount of downtime once the weapon system has failed?

The results presented in Chapter 4 show that PDM appears to reduce the number of failures per year from approximately 1.3 failures per year to less than one half of a failure per year. Although no confidence can be obtained from the Poisson regression, the model does suggest that PDM does reduce the number of failures per year. The hypothesis testing on the failure rates within each vehicle year group concludes PDM vehicle failure rates are significantly lower than no-PDM vehicle failure rates. The bootstrap technique further illustrates the reduction of failures per year for PDM vehicles.

The failure rate estimates for PDM and no-PDM vehicles obtained from all of the techniques used in Chapter 4 are consistent for each vehicle year group. Since both parametric and non-parametric techniques are used to obtain the failure rates, the consistency between the failure rates suggest that the failure rate estimates are close to the true failure rates.

The survivor curves for time to failure show significant differences between PDM and no-PDM vehicles. The PDM vehicles have a longer time between failures than the no-PDM vehicles. The survivor curves for the service time, except for the 1988 vehicles, are also significantly different for PDM vehicles and no-PDM vehicles. This indicates no-PDM vehicles remain in the maintenance facility materially longer than PDM vehicles.

The bootstrap estimates for downtime further validate the conclusions obtained from the survivor curve analysis. The bootstrap estimates reveal the magnitude of the differences between PDM vehicles and no-PDM vehicle downtime per year. No-PDM vehicles remain unserviceable for approximately 3.5 times longer than PDM vehicles and are down approximately 120 days a year.

Limitations of the Study

The Poisson regression model rejects the hypothesis that the model is Poisson. The model rejects this hypothesis because of the unexplained variability of the number of failures per year. Since YEARS SINCE LAST PDM has a small effect estimate, this variable does not significantly increase the number of failures per year and does not adequately capture usage. To reduce the unexplained variability and to obtain better effect estimates, a variable, or variables, must be introduced into this model that more accurately depict usage. Variables such as miles per year, hours of use per year, or type of mission of the vehicle might better explain the changing number of failures per year than YEARS SINCE LAST PDM.

The survivor curve estimates of the time to failure implicitly assume that the last failure before the date of request for PDM is a catastrophic failure, and the vehicle is immediately shipped to PDM. This implies no right censored data for vehicles that went through PDM. In the

case that a vehicle is working at the time of PDM, the amount of time the vehicle remained in service from its last failure to the date the vehicle was shipped to the depot should be considered a right censored data point. Instead, this time is added to the time for the first time to failure after PDM. This assumption will potentially decrease the time to failure survivor curve estimates for the no-PDM vehicles and increase the bootstrap estimates for failures per year.

In addition, the date of completion of the PDM is not available, so the time for the first failure after PDM also includes: shipping time to the depot, time in the depot, and shipping time back to the unit, as well as the out-of-service time. This over-estimation of the first time to failure after PDM will potentially increase the PDM time to failure survivor curve estimates and decrease the bootstrap estimates for failures per year. However, since the failures per year are consistent among all the techniques used in this study, apparently these assumptions did not dramatically effect the bootstrap estimates.

All the models in Chapter 4 assume a stationary failure rate, but the increase in the number of failures per year in 1994 and 1995 indicates the failure rates are rising. Because the number of failures per year is increasing with time, the effect estimates for the number of failures per year are understated. In order to obtain better effect estimates, failure data after 1993 should be analyzed separately because this is the point in time where the failure rate starts increasing.

Results and Implications

PDM significantly reduces the number of failures per year and substantially reduces the downtime per year. However, the results in Chapter 4 show relatively small failure rates for both PDM and no-PDM vehicles with high out of service times. As stated in Chapter 4, there are

several possible causes. The vehicles may be experiencing critical or catastrophic failures and are rebuilt at base level, or the supply system may not adequately re-supply the maintenance facilities.

Either scenario has direct implications to PDM. If the weapon system experiences a critical or catastrophic failure which requires PDM, the base level maintenance is not properly equipped to attempt the rebuild. The repair will occur either at base level or at the depot, but it has been shown that PDM is far preferable to a base level overhaul because PDM significantly reduces the number of failures per year.

There is evidence that indicates the supply system is experiencing difficulties in supporting the LVS. The Marine Corps LVS item manager stated that there existed a supply problem with the LVS, and many parts have a large lead time between a part request and delivery. If the current supply system can not adequately re-supply the maintenance facilities, reducing the number of failures per year with the PDM program will significantly increase weapon system availability. Since these vehicles are aging and nearing their mid-life rebuild, these vehicles will inevitably experience more critical or catastrophic failures per year. With any increase in these types of failures per year, the projected effect on the supply system will only further reduce the availability of the LVS and make PDM even more critical.

The cost for PDM, regardless of the actual maintenance performed on a weapon system, is considered a fixed cost. The PDM cost for the LVS is $72,157 for the depot located Albany, Georgia and $75,494 for the depot located in Barstow, California (Lydia Burch, 1996). The current price for procurement of a new LVS is approximately $172,000 plus $9,000 for additional spare parts. Thus, the total cost of a new LVS is approximately $181,000. These prices are based on the procurement of 42 to 45 LVSs (Joe Littleton, 1996). The increase in availability, if

PDM is performed, is approximately 24.7 percent $\left(\frac{120-30}{365}\right)$. The downtime for a no-PDM

vehicle is approximately 120 days and the downtime for a PDM vehicle is approximately 30 days.

If 200 vehicles are scheduled for PDM, but are not funded, approximately 54 vehicles need to be

procured to obtain the same availability $\left(\frac{200(.247)}{.918}\right)$. Note, the availability of a PDM vehicle is

91.8 percent, and PDM vehicles exhibit failure rates similar to new vehicles. The cost for

procuring 54 vehicles is approximately $9.8 million, and the cost for the PDM is approximately

$14.8 million.

However, this analysis does not take into account the cost of maintenance at the base

level. Furthermore, adding 54 vehicles to the fleet only temporarily maintains availability and

masks the real issue. This solution increases the demands placed on a supply system that currently

can not support the fleet, and the 200 no-PDM vehicles will continue to deteriorate. In addition,

this analysis assumes that the availability of the no-PDM vehicles remains constant the next year,

but this research has shown that the failure rate is increasing.

As more no-PDM LVS's experience critical or catastrophic failures and as the demand for

replacement parts increase, the availability of the no-PDM LVS will inevitable decrease further.

When the availability of the no-PDM LVS decreases from 67.1 to 54.2 percent, the procurement

costs and PDM costs will yield the same availability. Procuring replacement vehicles until the

availability rate reaches 54.2 percent is not cost effective.

Recommendations for Follow-on Research

This research study is limited by the assumptions made about the data and the assumptions of a Poisson process. Although the results conclude that PDM is significant in reducing the number of failures per year and increasing the availability of the LVS, these estimates for number of failures per year and downtime per year are conservative.

More attention to detail should be used in the data collection process. First, the Marine Corps depot needs an automated data base to provide an audit trail for a weapon system through the depot. Data such as the date a weapon system is received in the depot and the date a weapon system is shipped back to the unit should be included in the data base. A maintenance history should show the depot maintenance performed on the weapon system. These data can support analysis to determine if maintenance in the field had to be re-accomplished at the depot. The manufacturing date of the LVS is imperative in determining the age of the system and the Marine Corps currently does not track this date.

In order to obtain better effect estimates for the Poisson regression, a variable such as mileage per year or hours of use per year should capture usage. Currently, data are only collected upon failure. A model such as the one proposed in Chapter 3 requires mileage or usage per year. A variable such as mission type or location would also help explain the number of failures per year because there are a variety of missions in the Marine Corps.

Finally, there is evidence that suggests the number of failures per year is increasing in 1994 and 1995. A follow on study should focus on failure data after 1993. The effect estimates would better represent the current status of the weapon system and would not be biased by the lower failure rates experienced in 1990-1993.

Comparison of Yr 85 no-PDM Failure Distribution and Poisson(1.01)
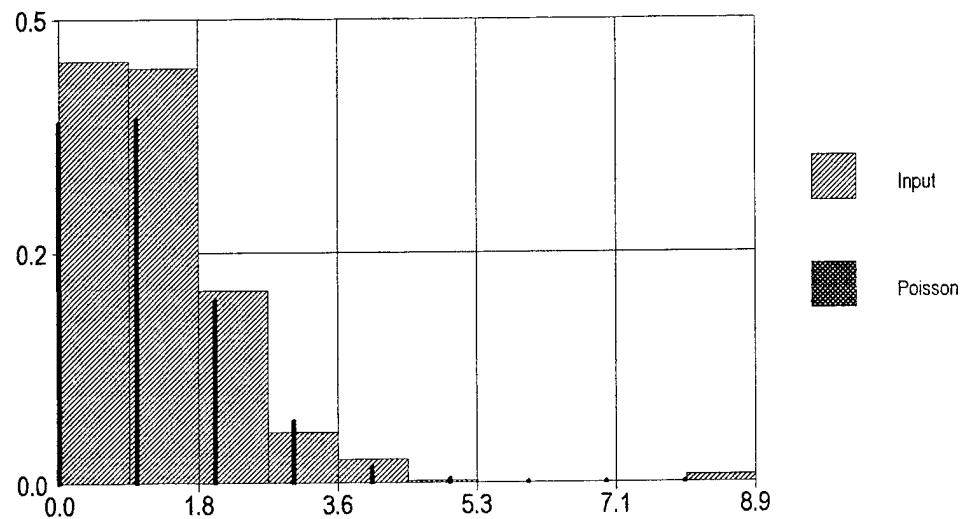
Comparison of Yr 85 PDM Failure Distribution and Poisson(0.28)
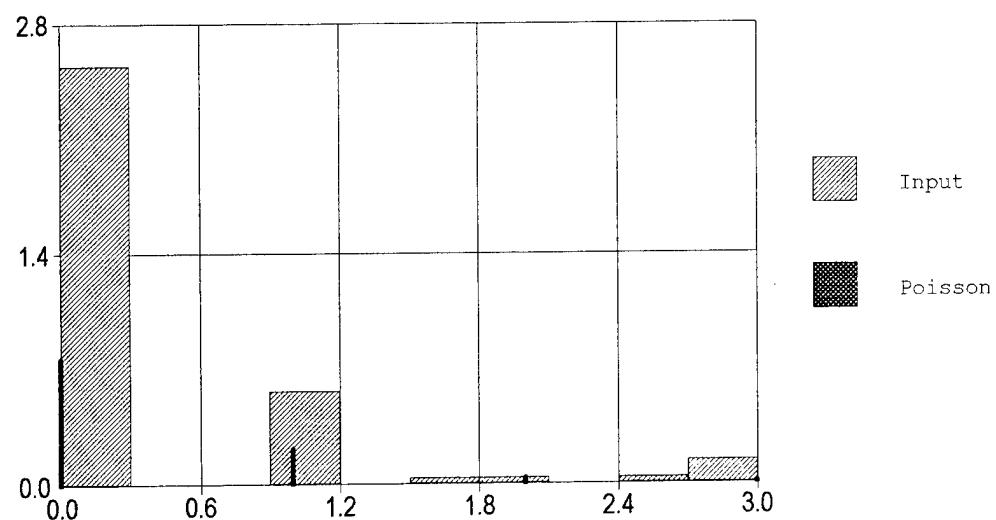
Comparison of Yr 86 no-PDM Failure Distribution and Poisson(0.97)
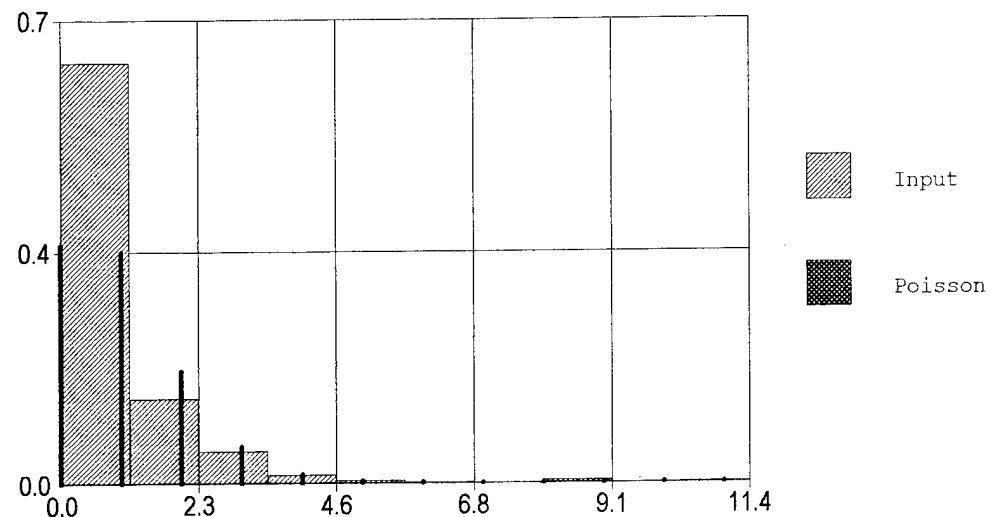

## Comparison of Yr 86 PDM Failure Distribution and Poisson(0.26)
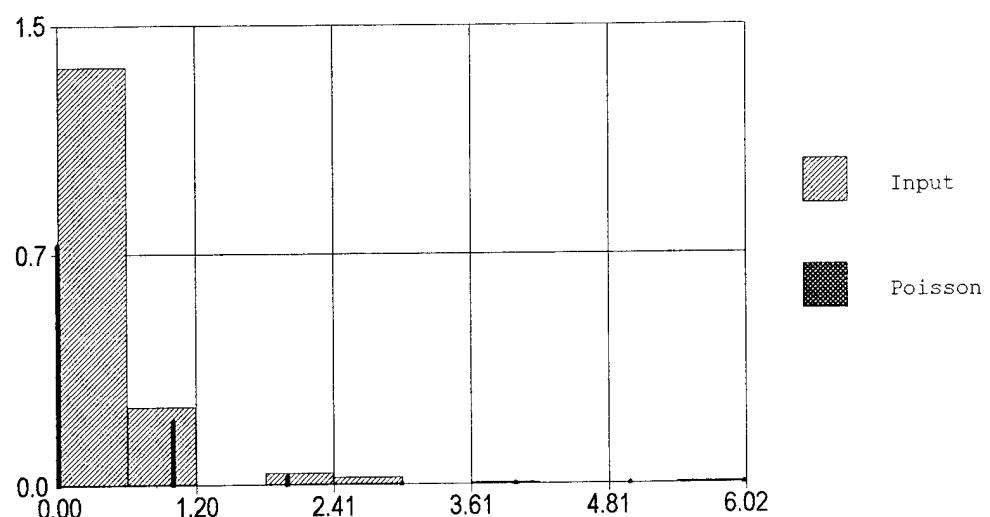
## Comparison of Yr 87 no-PDM Failure Distribution and Poisson(1.22)
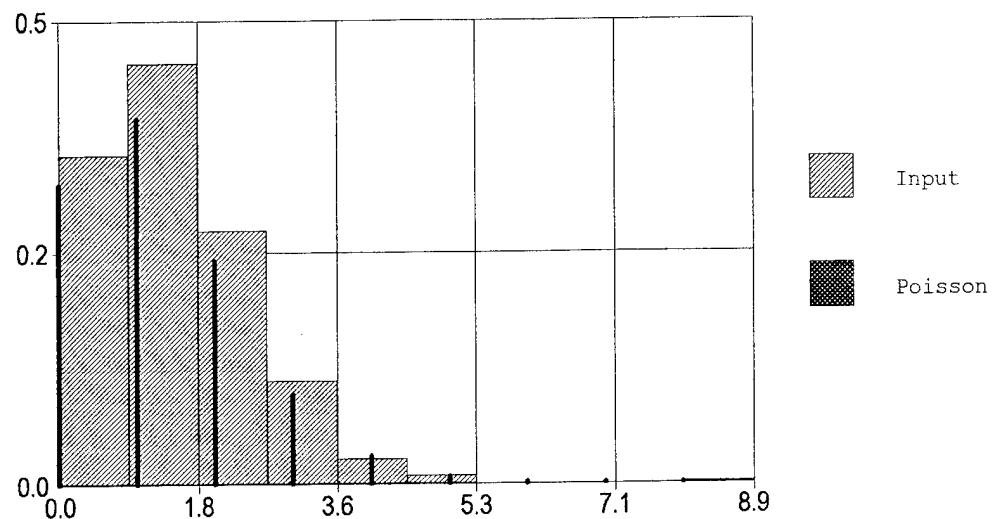
## Comparison of Yr 87 PDM Failure Distribution and Poisson(0.30)
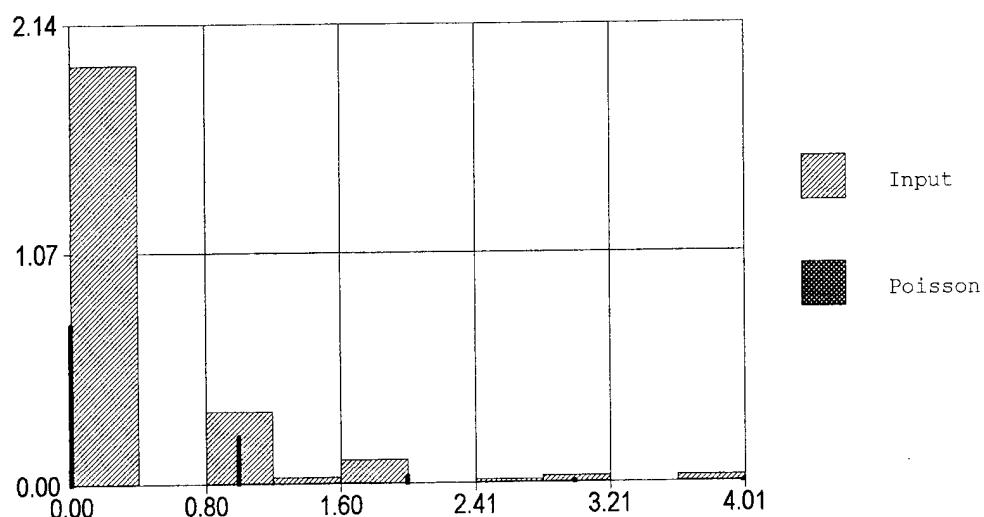
Comparison of Yr 88 no-PDM Failure Distribution and Poisson(1.08)
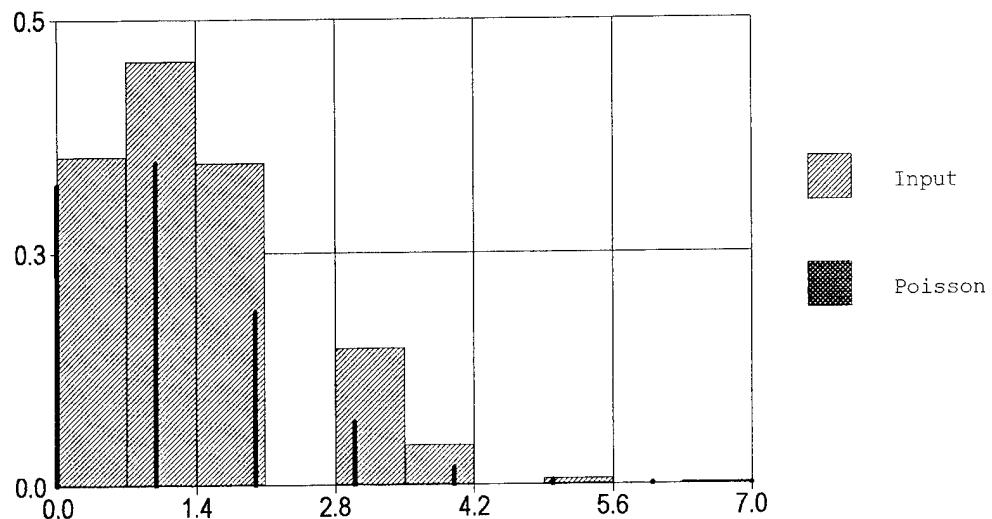
Comparison of Yr 88 PDM Failure Distribution and Poisson(0.34)
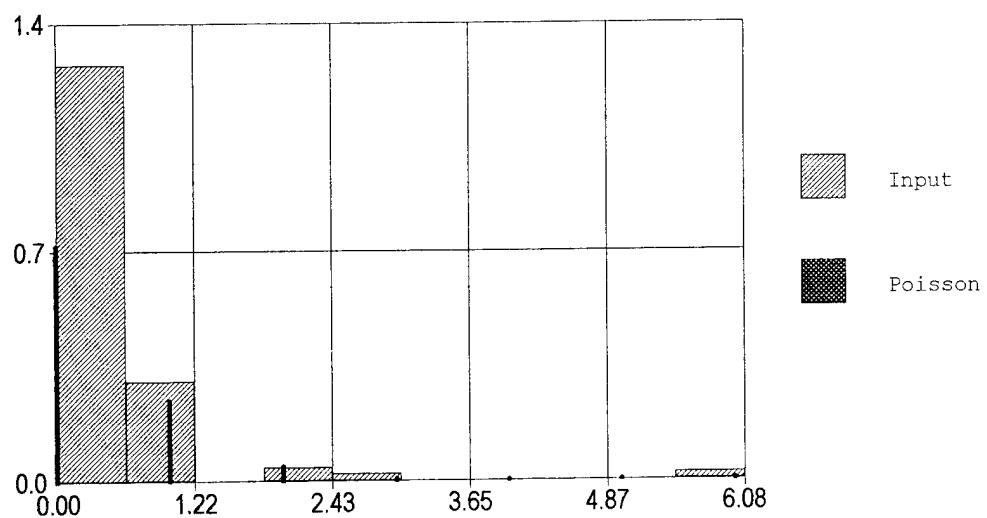
Comparison of Yr 89 no-PDM Failure Distribution and Poisson(4.48e-5)

Values in 10^-1

Input

Poisson
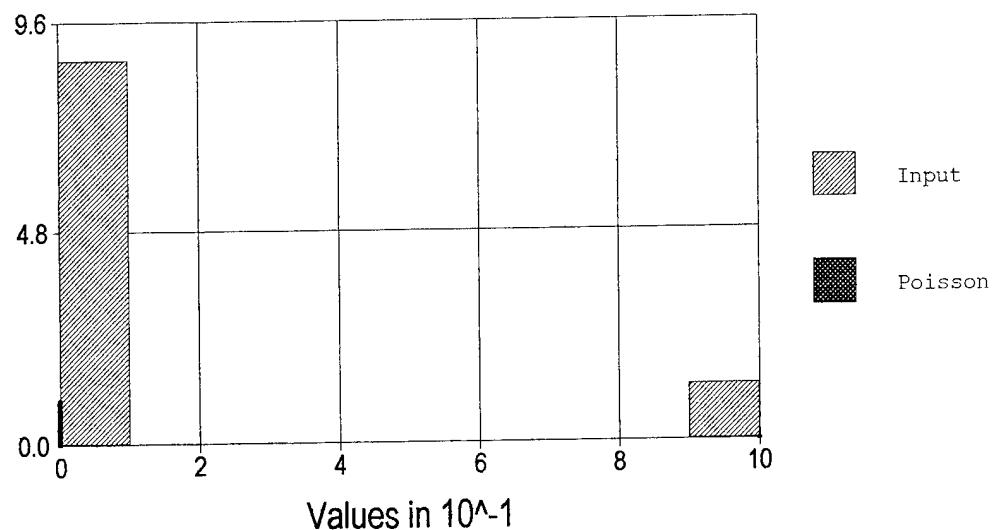
APPENDIX B: Scatter Plot of the Number of Failures per Year per Group

Scatter Plot of NUMFAIL vs GROUP-YEAR

GROUP-YEAR
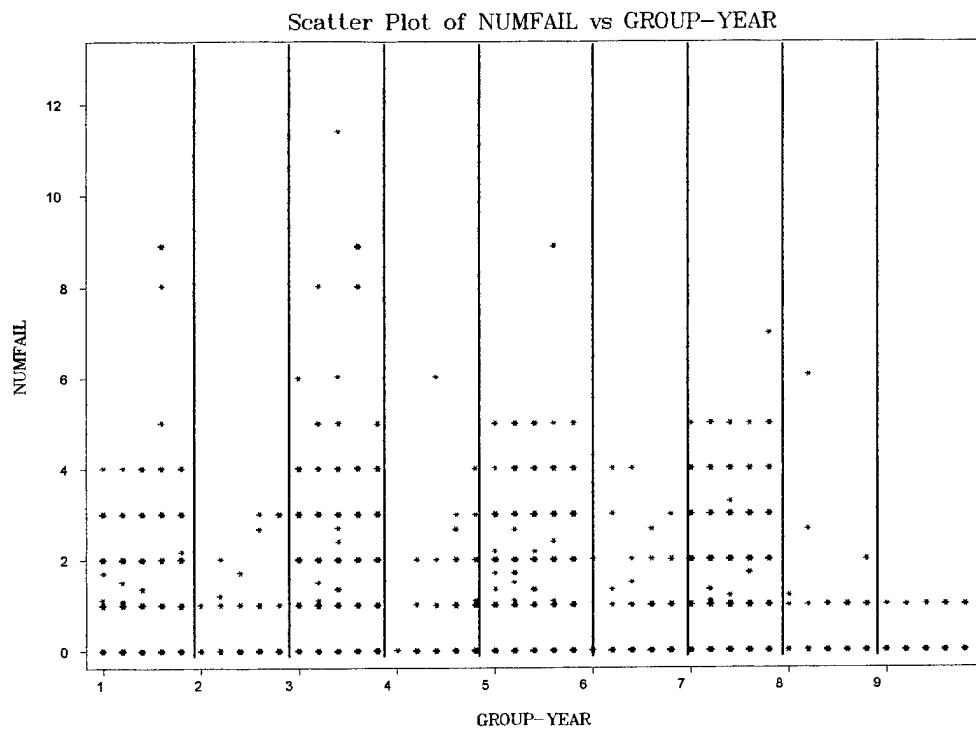
Group 1 is 1985 year vehicles with no-PDM.
Group 2 is 1985 year vehicles with PDM.
Group 3 is 1986 year vehicles with no-PDM.
Group 4 is 1986 year vehicles with PDM.
Group 5 is 1987 year vehicles with no-PDM.
Group 6 is 1987 year vehicles with PDM.
Group 7 is 1988 year vehicles with no-PDM.
Group 8 is 1988 year vehicles with PDM.
Group 9 is 1989 year vehicles with no-PDM.

The first column represents the failures occurring in the year 1990.
The second column represents the failures occurring in the year 1991.
The third column represents the failures occurring in the year 1992.
The forth column represents the failures occurring in the year 1993.
The fifth column represents the failures occurring in the year 1994.

# APPENDIX C: Graphs of Uniform Distributions

YEAR 90 FAILURES
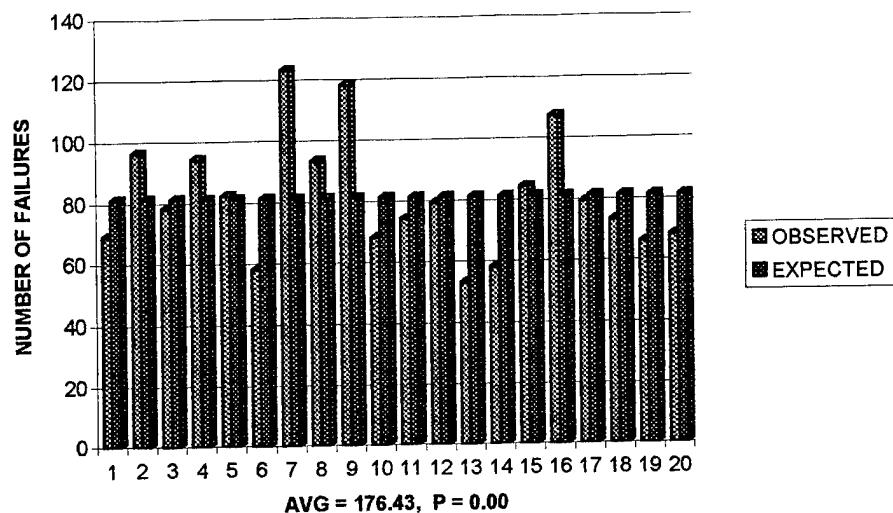
AVG = 176.43, P = 0.00

YEAR 91 FAILURES

AVG = 175.03, P = 0.00

YEAR 92 FAILURES

AVG = 181.65, P = 0.00

YEAR 93 FAILURES

AVG = 167.09, P = 0.00

59

YEAR 94 FAILURES

AVG = 180.49, P = 0.00

YEAR 95 FAILURES

AVG = 159.78, P = 0.00
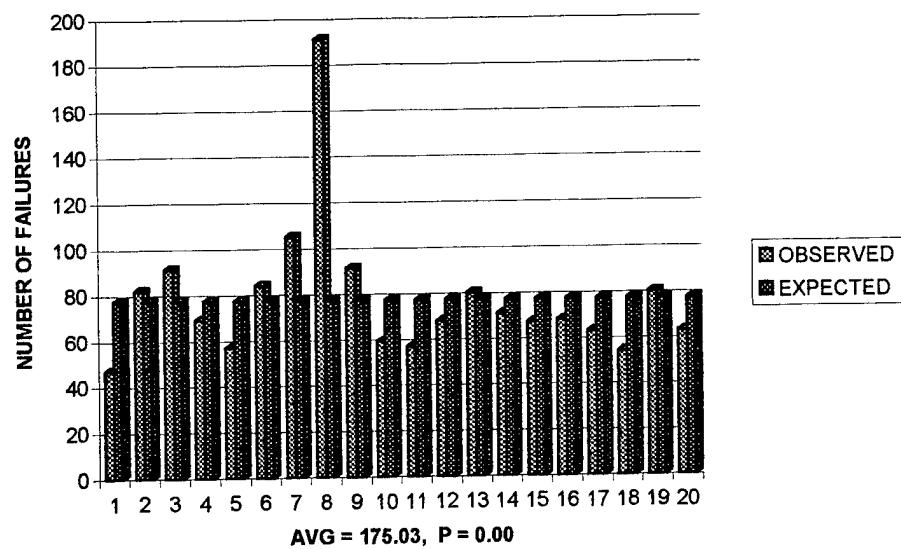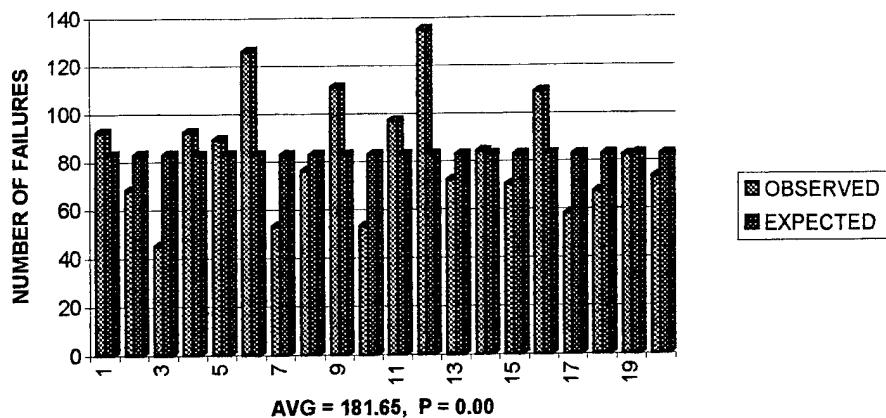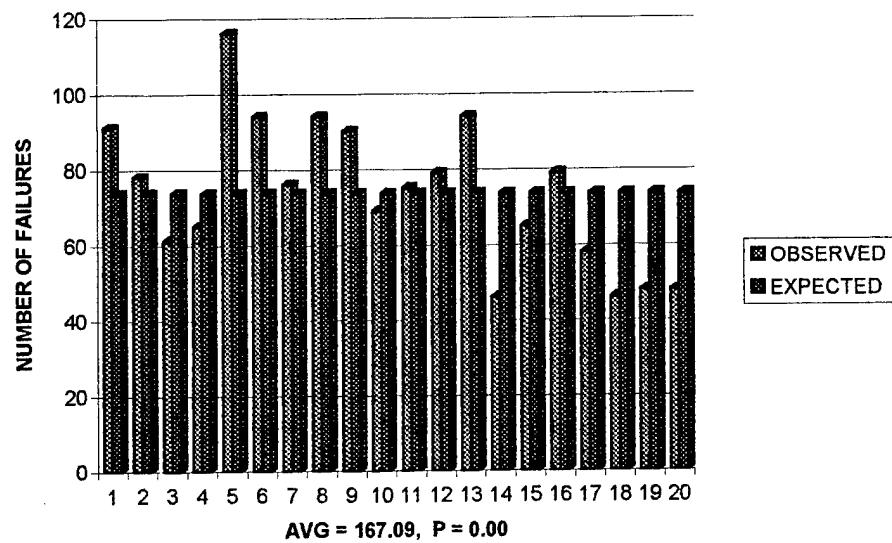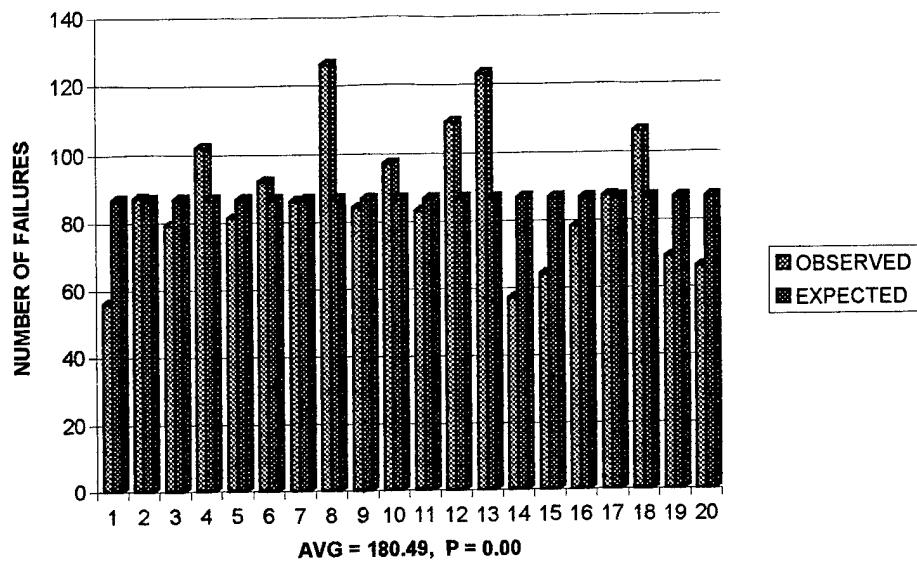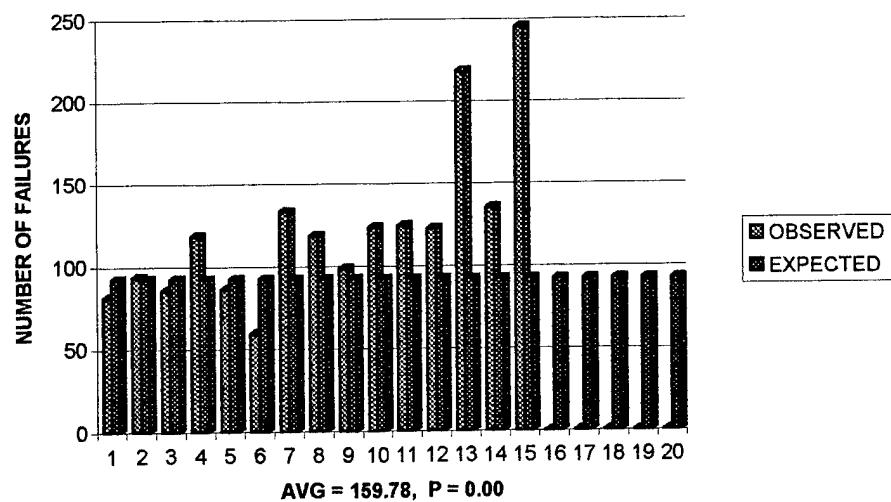
# APPENDIX D: Scatter Plot of the Residuals with Number of Failures per Year and the Wilk-Shipiro Rankit Plot

Scatter Plot of RES vs NUMFAIL

Wilk–Shapiro / Rankit Plot of RES
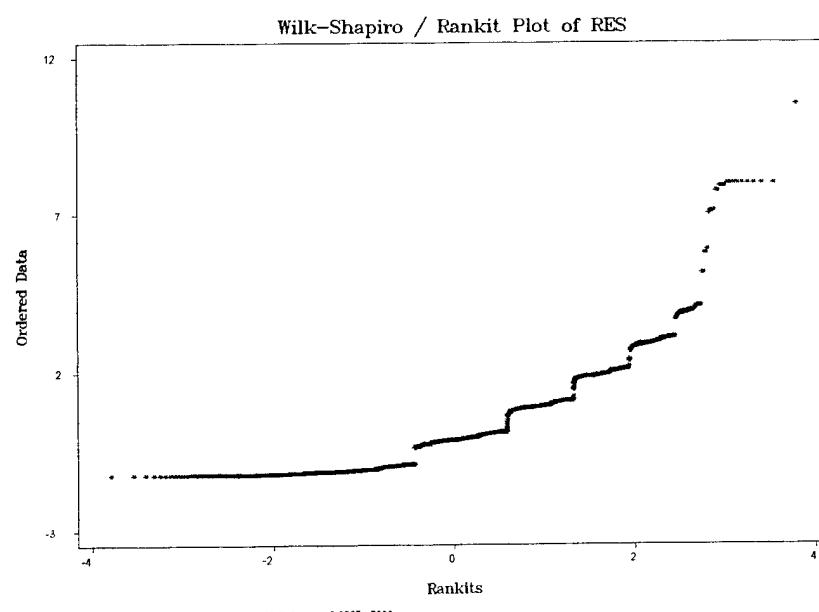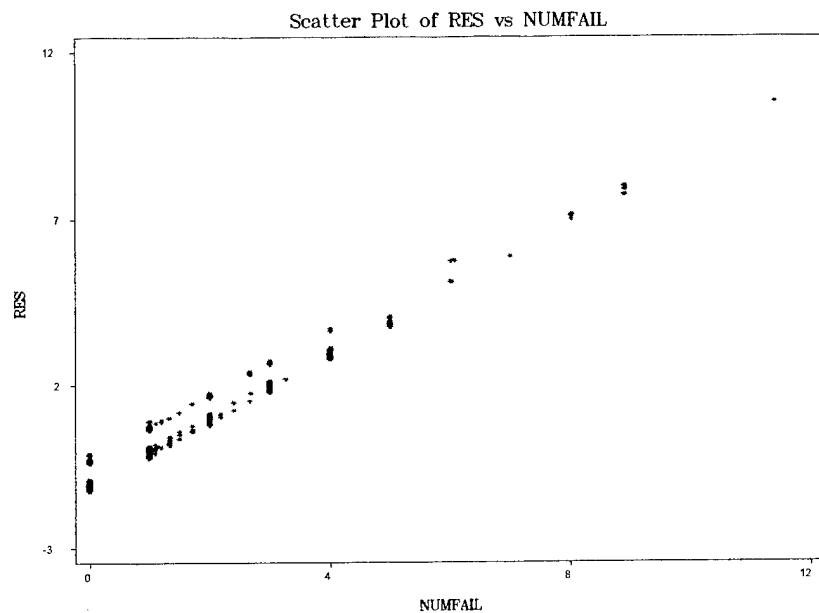
Approximate Wilk-Shapiro 0.8505   7839 cases

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APPENDIX E: Scatter Plot of the Residuals with the Independent Variables and Fitted Values

Scatter Plot of RES vs PDM

Scatter Plot of RES vs FIT

Scatter Plot of RES vs GROUP

Scatter Plot of RES vs YRAFTPDM
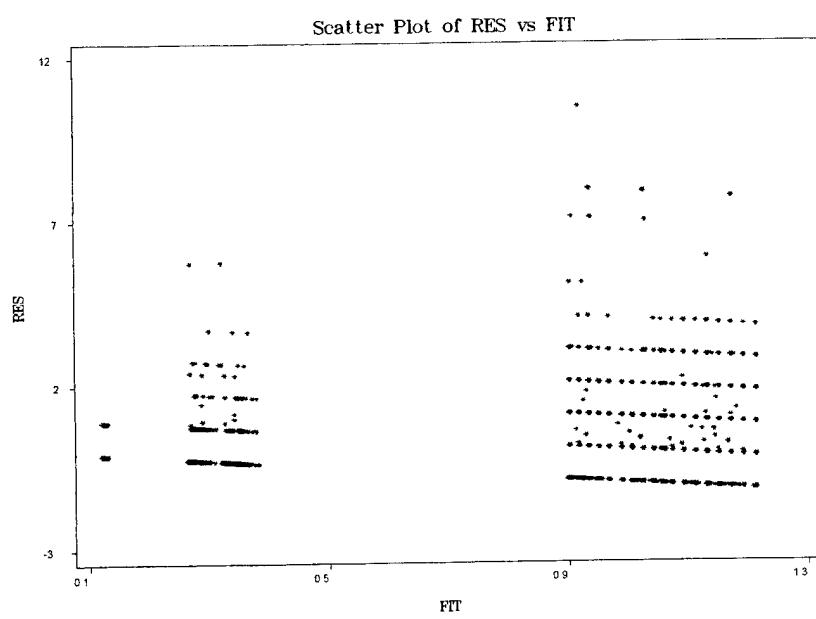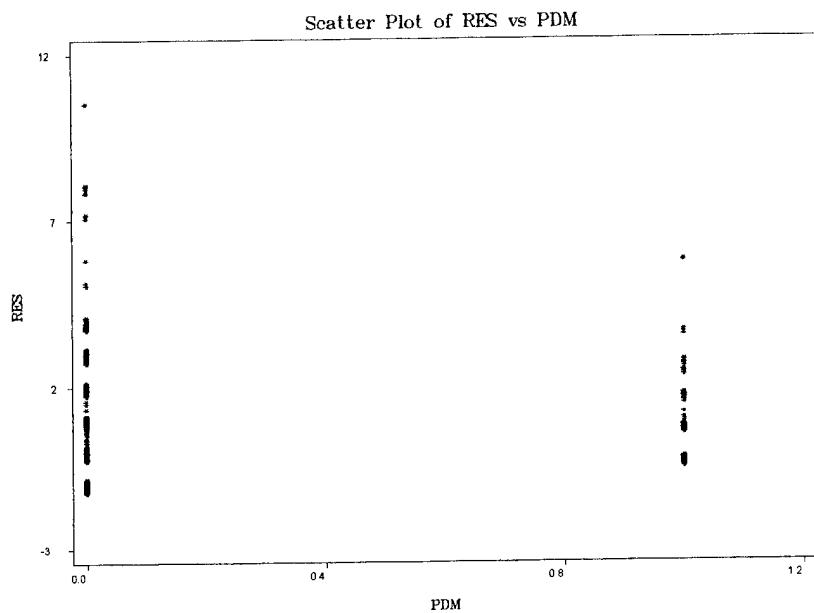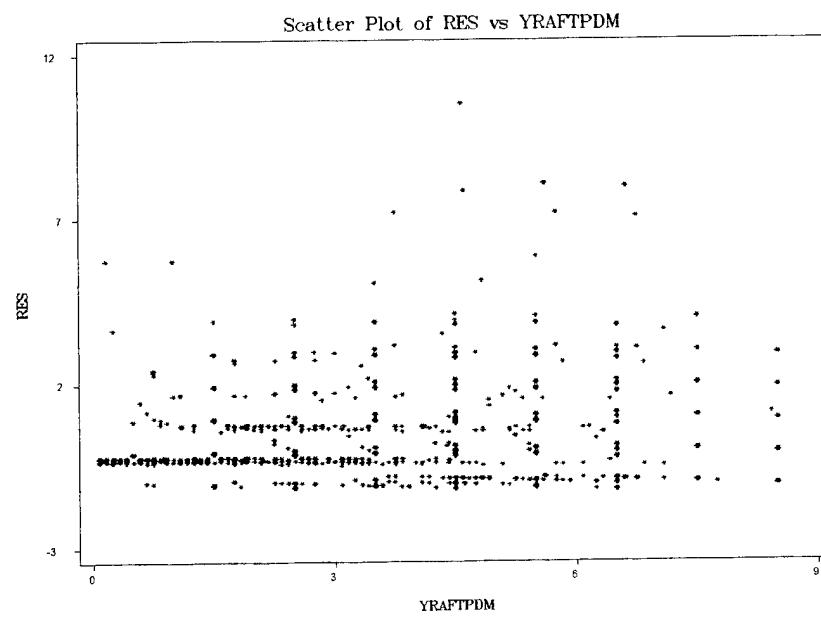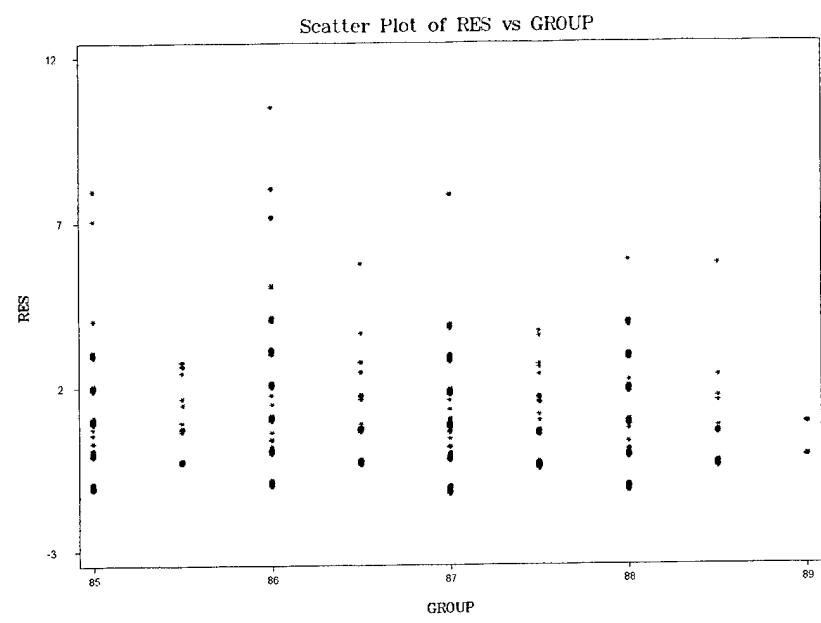
Appendix F: Results of the Hypothesis Testing for PDM and no-PDM Kaplan-Meier Survivor Curves

Year 85 vehicles time to failure curves

Log rank test

	N	Observed	Expected	(O-E)^2/E
NOPDM	743	554	504.76	4.803
PDM	66	38	87.24	27.789

Chisq=34.5
p=0.000000004206
Result: Reject H_0 with α = .05

Peto-Peto modification

	N	Observed	Expected	(O-E)^2/E
NOPDM	743	330.11	307.61	1.645
PDM	66	17.99	40.49	12.499

Chisq=22.6
p=0.000001968
Result: Reject H_0 with α = .05

Year 86 vehicles time to failure curves

Log rank test

	N	Observed	Expected	(O-E)^2/E
NOPDM	2465	1741	1588.4	14.66
PDM	197	98	250.6	92.92

Chisq=113.6
p=0
Result: Reject H_0 with α = .05

Peto-Peto modification

	N	Observed	Expected	(O-E)^2/E
NOPDM	2465	1093.73	1013.9	6.289
PDM	197	45.98	125.8	50.67

Chisq=91.8
p=0
Result: Reject H_0 with α = .05

Year 87 vehicles time to failure curves

Log rank test

	N	Observed	Expected	(O-E)^2/E
NOPDM	2956	2261	2168.8	3.92
PDM	115	64	156.2	54.43

Chisq=60.9
p=0.000000000000005884
Result: Reject H_0 with α = .05

Peto-Peto modification

	N	Observed	Expected	(O-E)^2/E
NOPDM	2956	1329.4	1293.02	1.025
PDM	115	33.1	69.51	19.075

Chisq=32.7
p=0.00000001072
Result: Reject H_0 with α = .05

Year 88 vehicles time to failure curves

Log rank test

	N	Observed	Expected	(O-E)^2/E
NOPDM	3231	2360	2318.14	0.756
PDM	49	23	64.86	27.018

Chisq=28.2
p=0.0000001114
Result: Reject H_0 with α = .05

Peto-Peto modification

	N	Observed	Expected	(O-E)^2/E
NOPDM	3231	1438.143	1416.19	0.3403
PDM	49	9.905	31.86	15.1275

Chisq=25.1
p=0.0000005389
Result: Reject H_0 with α = .05

Year 85 vehicles service time curves

Log rank test

	N	Observed	Expected	(O-E)^2/E
NOPDM	688	688	701.81	0.2717
PDM	39	39	25.19	7.5697

Chisq=7.9
p=0.004813
Result: Reject H_0 with α = .05

Peto-Peto modification

	N	Observed	Expected	(O-E)^2/E
NOPDM	688	341.49	350.81	0.2473
PDM	39	24.29	14.98	5.7919

Chisq=8.6
p=0.003445
Result: Reject H_0 with α = .05

Year 86 vehicles service time curves

Log rank test

	N	Observed	Expected	(O-E)^2/E
NOPDM	2206	2206	2263.08	1.44
PDM	108	108	50.92	63.99

Chisq=66.4
p=0.0000000000000003331
Result: Reject H_0 with α = .05

Peto-Peto modification

	N	Observed	Expected	(O-E)^2/E
NOPDM	2206	1086.13	1131.88	1.849
PDM	108	77.36	31.61	66.208

Chisq=92.5
p=0
Result: Reject H_0 with α = .05

Year 87 vehicles service time curves

Log rank test

	N	Observed	Expected	(O-E)^2/E
NOPDM	2679	2679	2694.6	0.0903
PDM	72	72	56.4	4.3143

Chisq=4.4
p=0.03491
Result: Reject H_0 with α = .05

Peto-Peto modification

	N	Observed	Expected	(O-E)^2/E
NOPDM	2679	1342.35	1351.67	0.06424
PDM	72	40.86	31.54	2.75338

Chisq=4
p=0.04438
Result: Reject H_0 with α = .05

Year 88 vehicles service time curves

Log rank test

	N	Observed	Expected	(O-E)^2/E
NOPDM	2829	2829	2827.66	0.000639
PDM	26	26	27.34	0.066104

Chisq=.01
p=0.795
Result: Do not Reject H_0 with α = .05

Peto-Peto modification

	N	Observed	Expected	(O-E)^2/E
NOPDM	2829	1422.7	1425.02	0.003792
PDM	26	14.27	11.94	0.452543

Chisq=0.7
p=0.4013
Result: Do not Reject H_0 with α = .05

Survivor Curve for the 85 Year LVS'S

Surviving Time in Days

Proportion Surviving

NO PDM
PDM
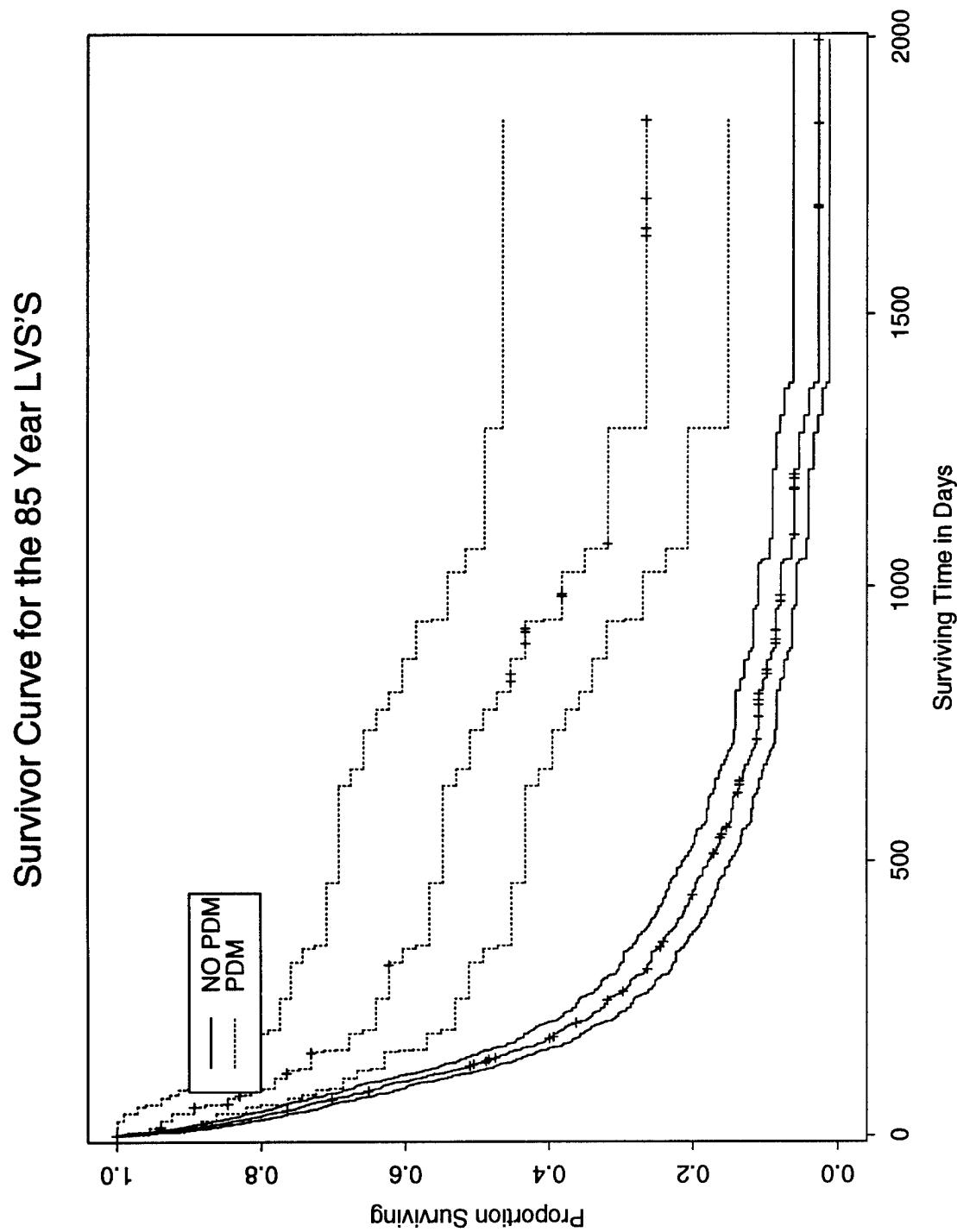
Survivor Curve for the 86 Year LVS'S
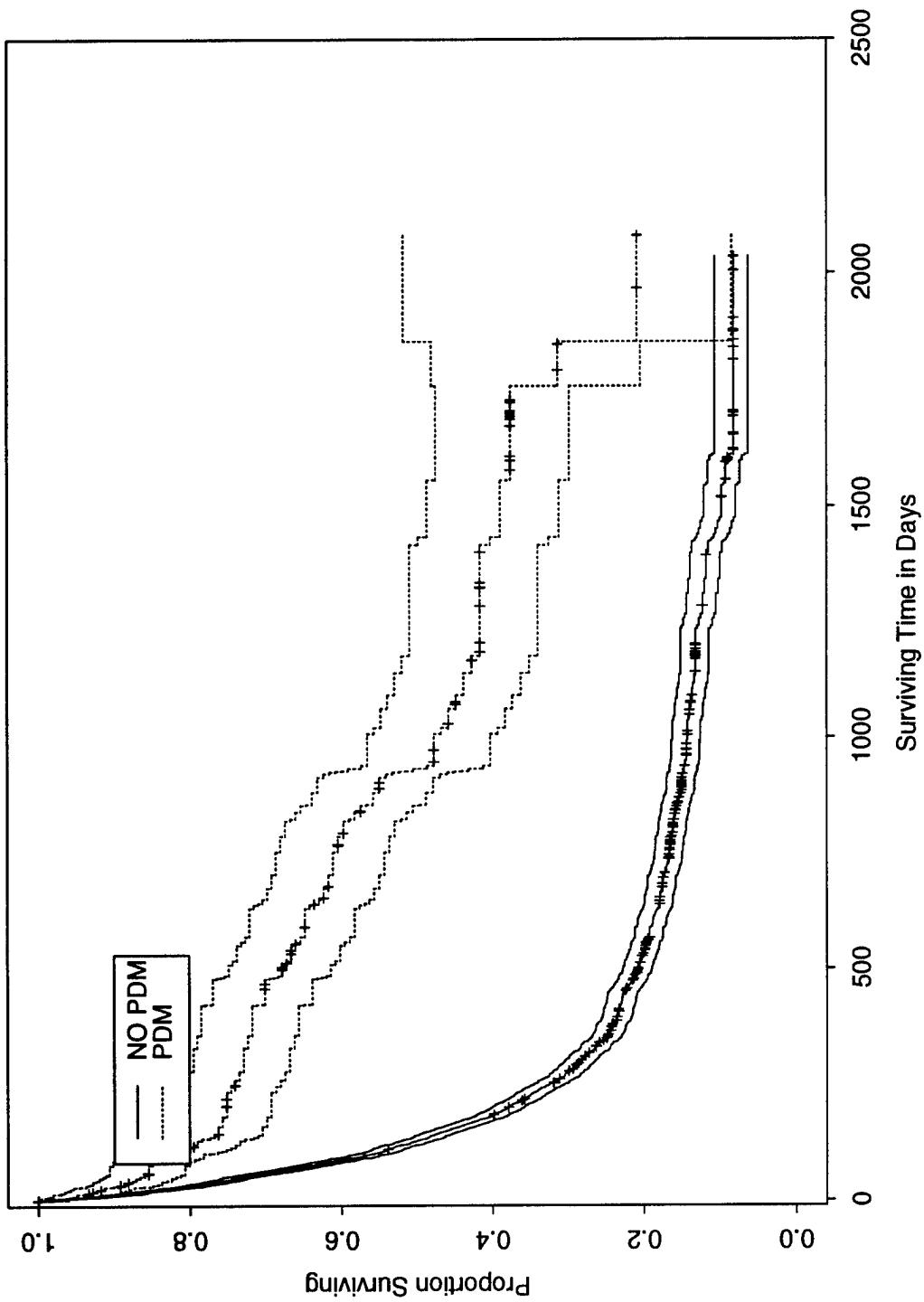
Survivor Curve for the 87 Year LVS'S
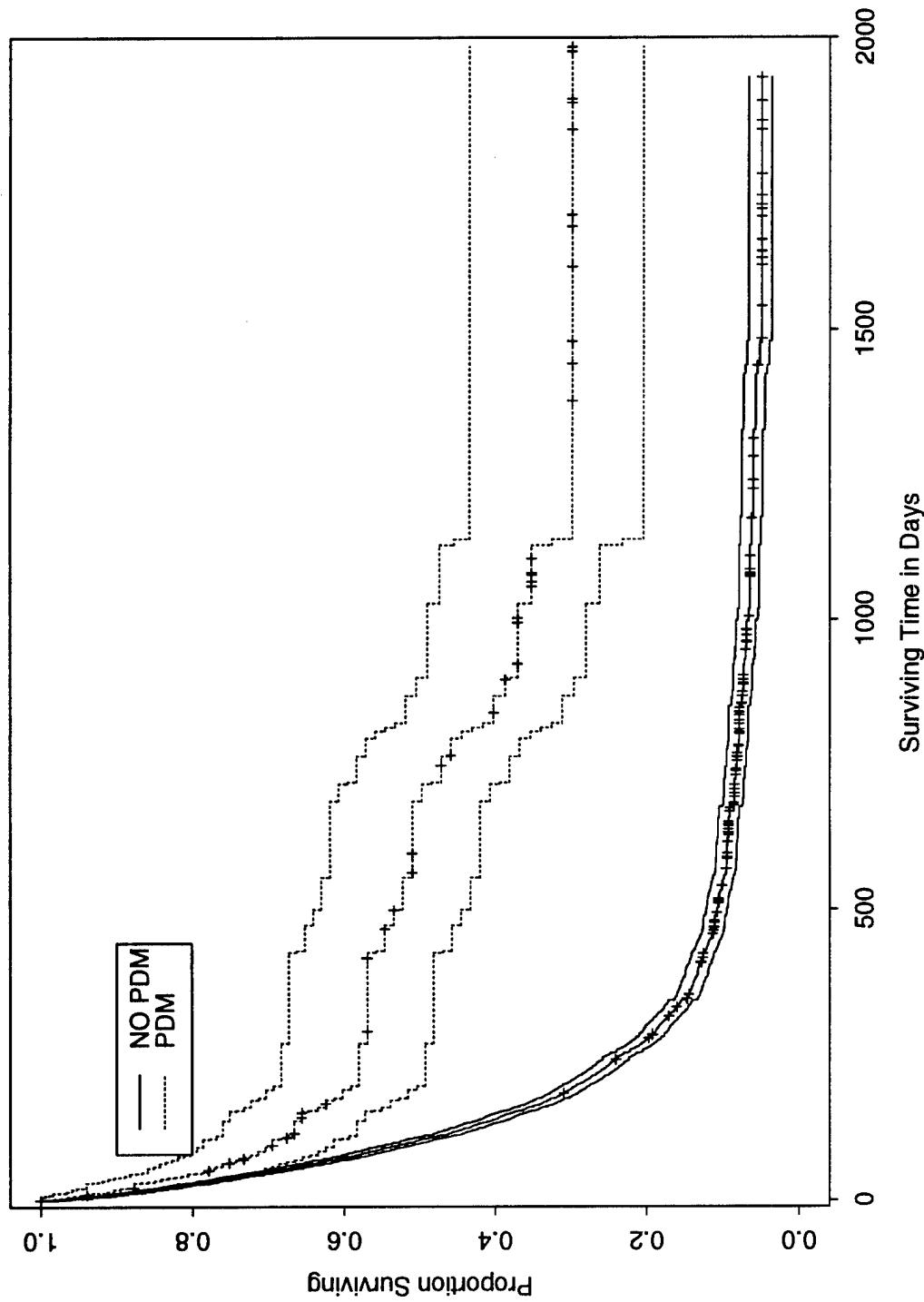
Survivor Curve for the 88 Year LVS'S

Survivor Curve for the 89 Year LVS'S

Surviving Time in Days

Proportion Surviving
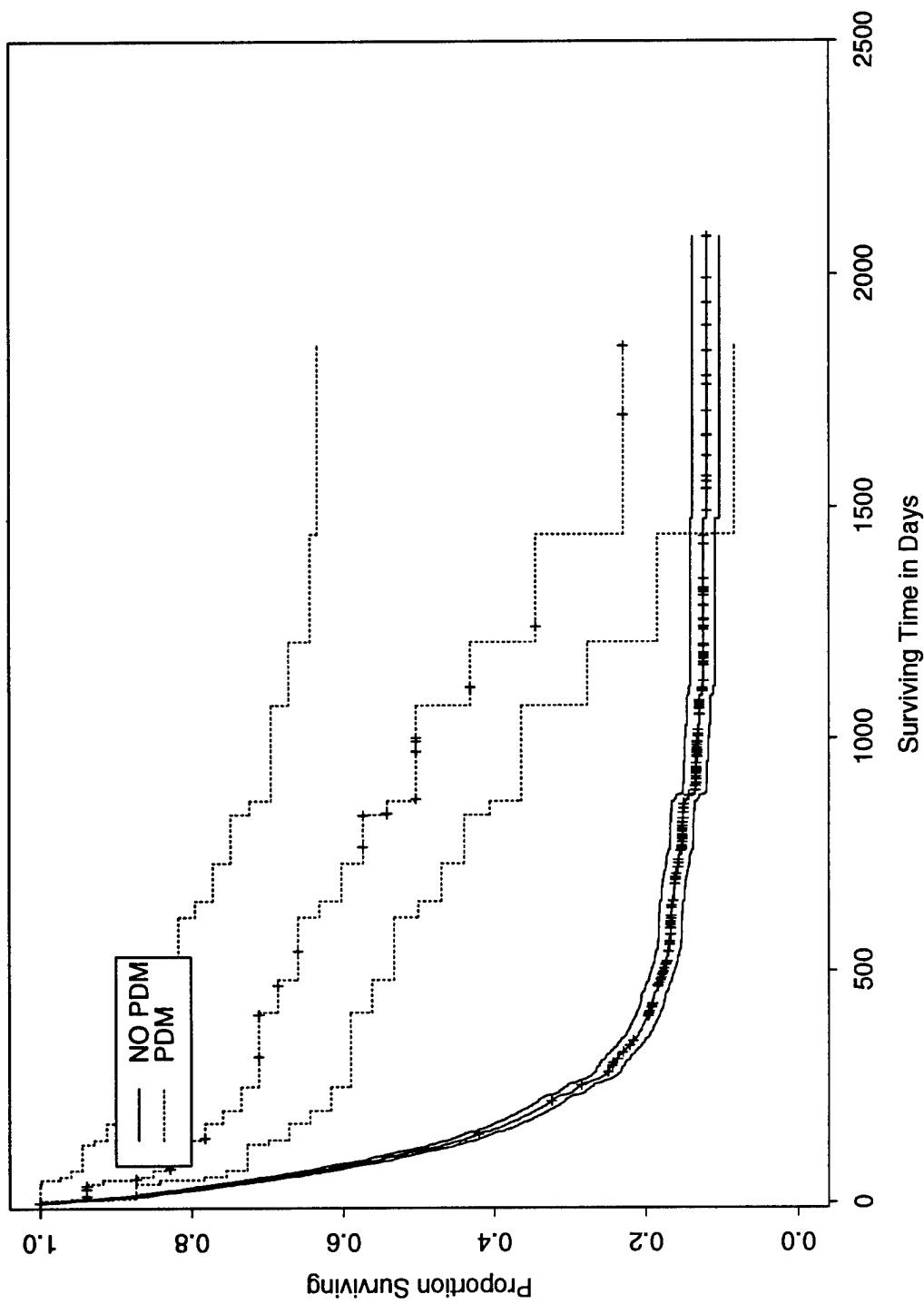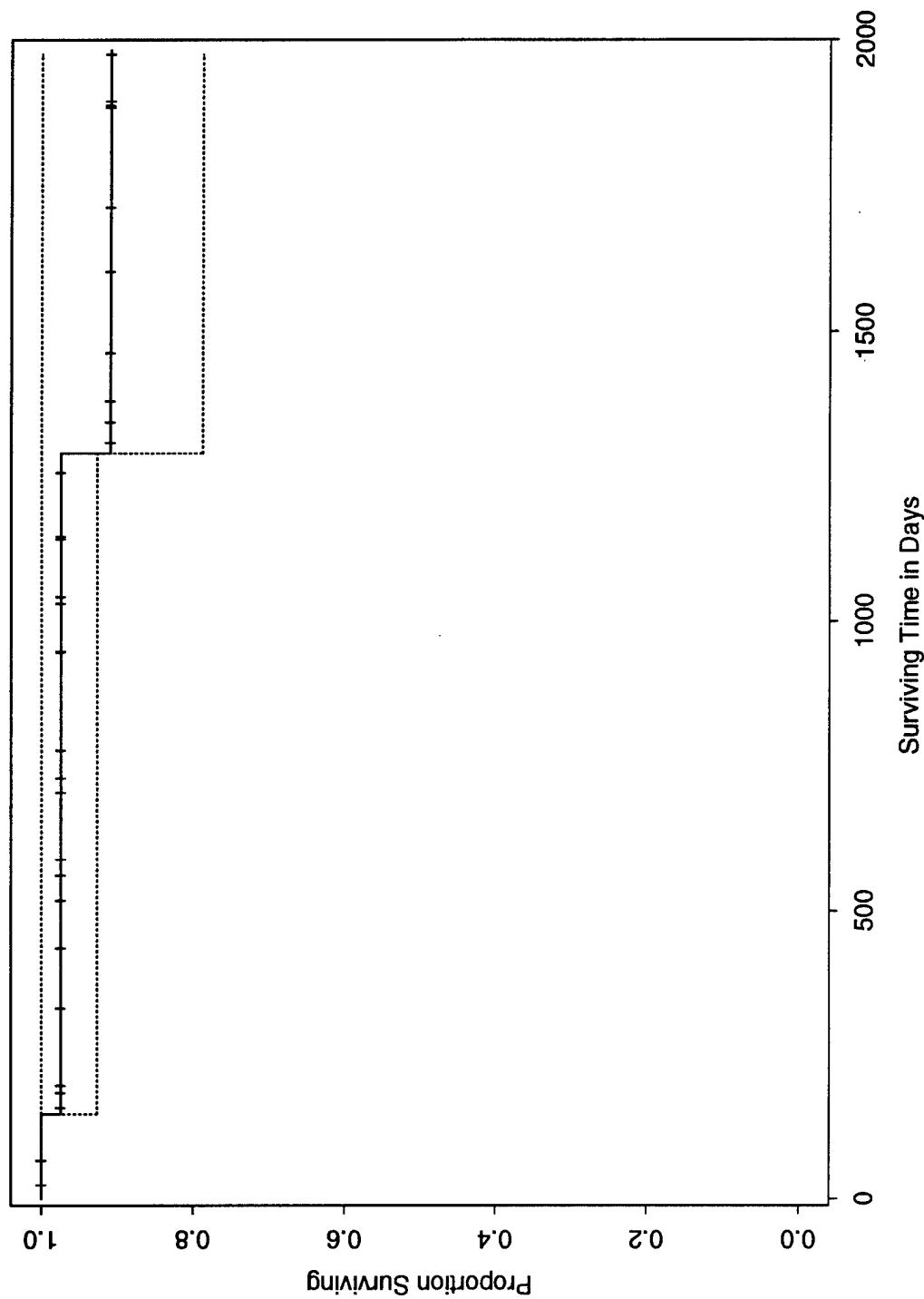
Service Time Curve for the 85 Year LVS'S
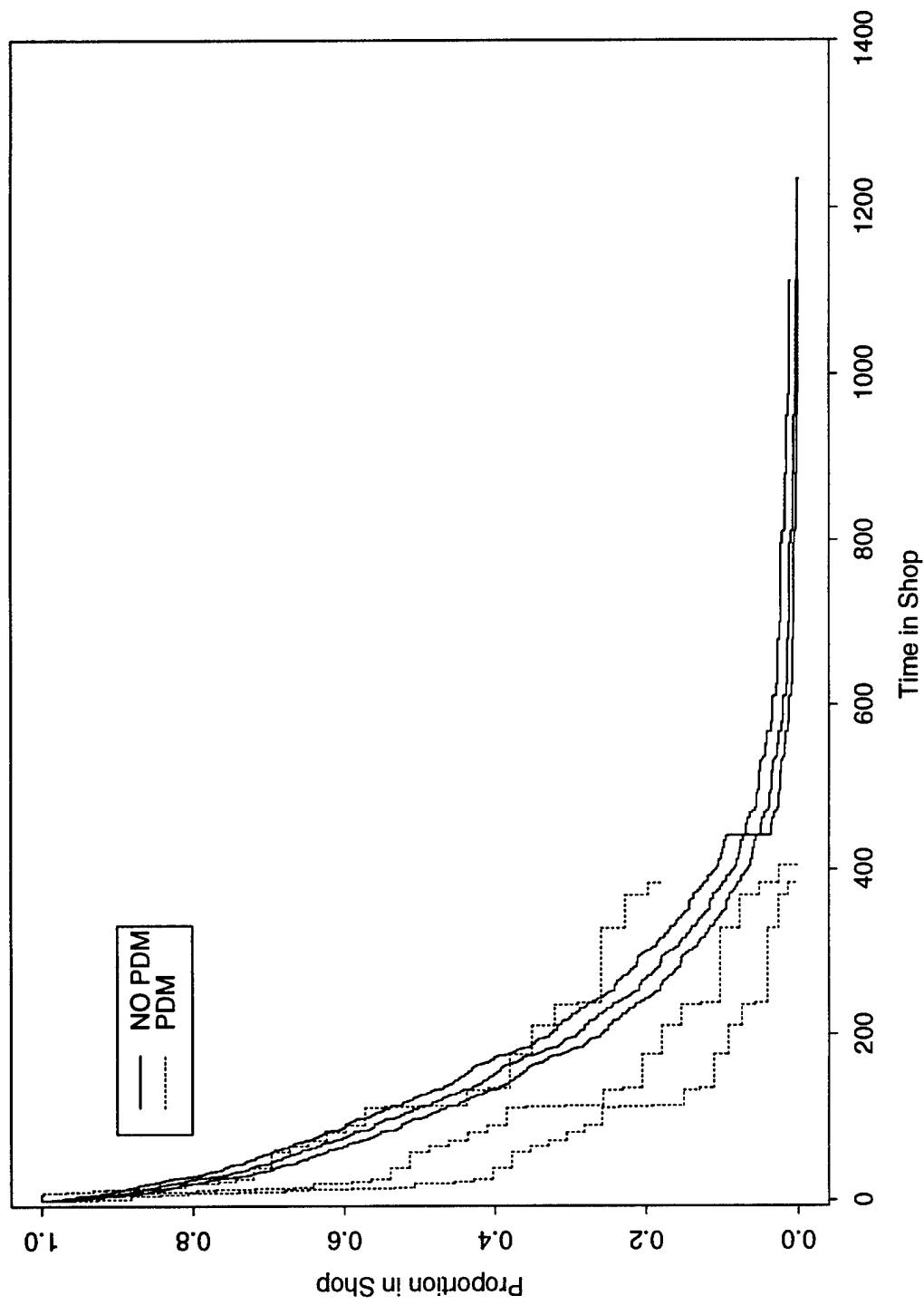
Service Time Curve for the 86 Year LVS'S
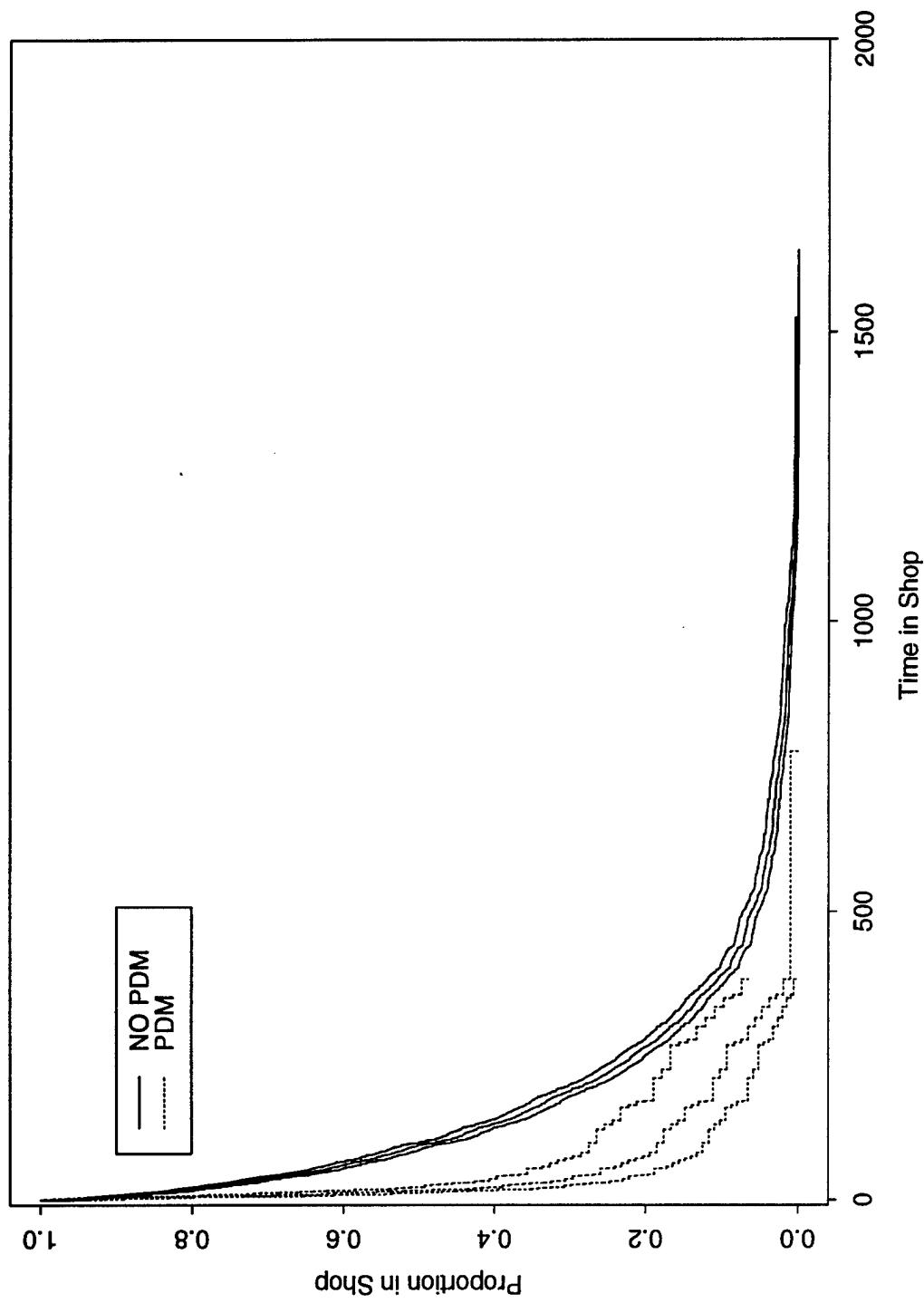
Service Time Curve for the 87 Year LVS'S
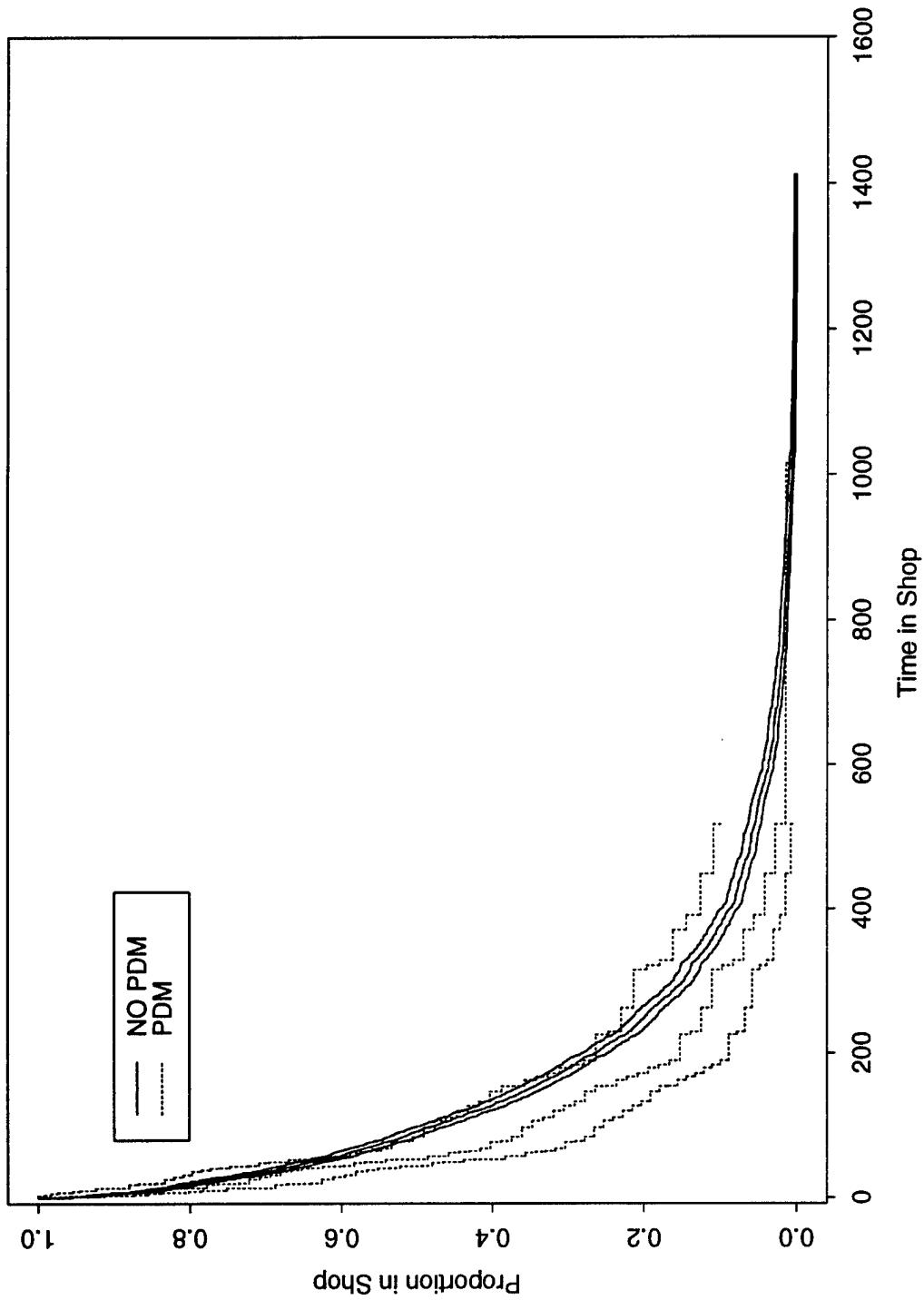
Service Time Curve for the 88 Year LVS'S

Survivor Curve for the 89 Year LVS'S

Proportion Surviving

Surviving Time in Days

Survivor Curves for the LVS

Legend:
- 85
- 85 PDM
- 86
- 86 PDM
- 87
- 87 PDM
- 88
- 88 PDM
- 89

X-axis: Surviving Time in Days (0, 500, 1000, 1500, 2000, 2500)

Y-axis: Proportion Surviving (0.0, 0.2, 0.4, 0.6, 0.8, 1.0)
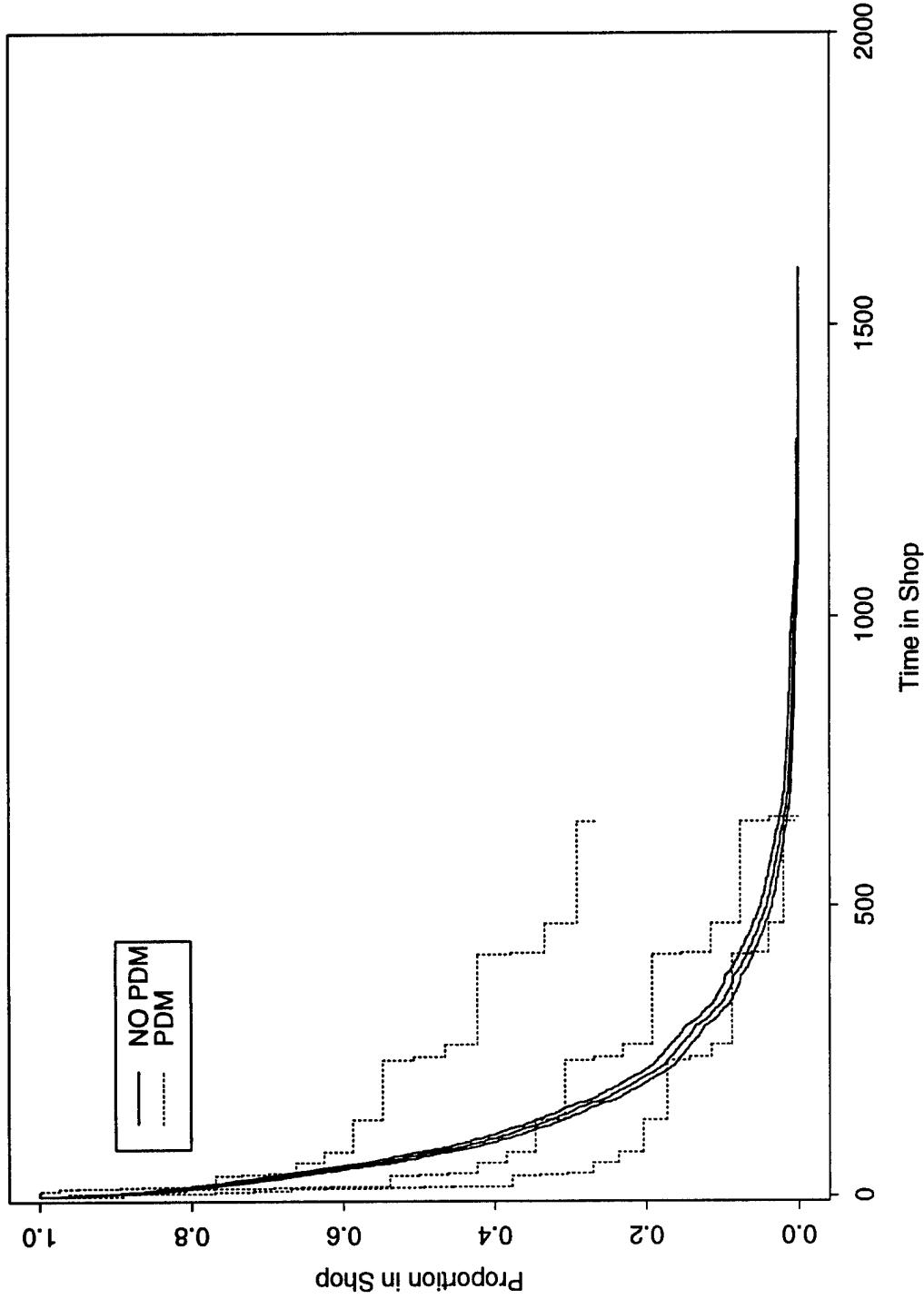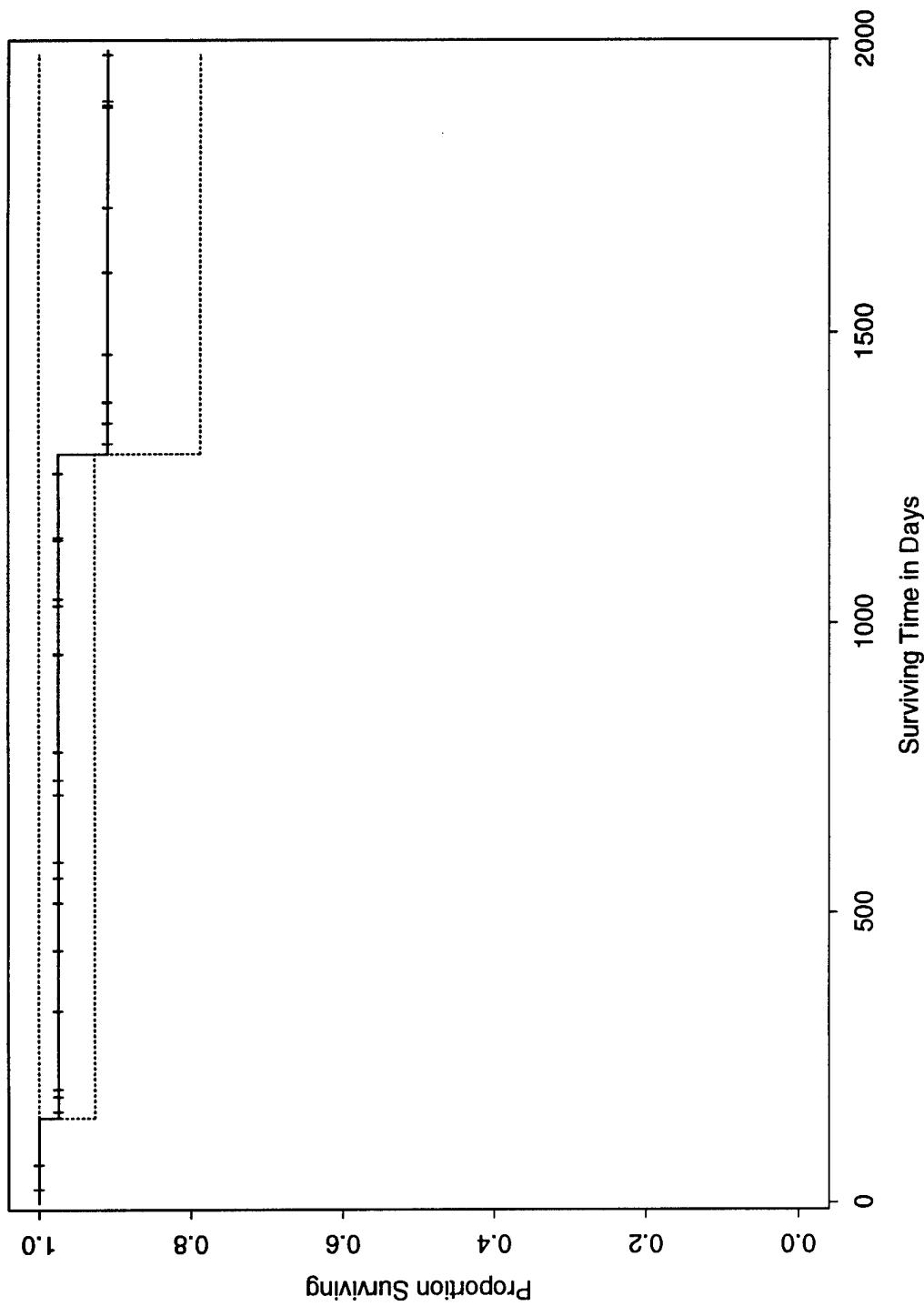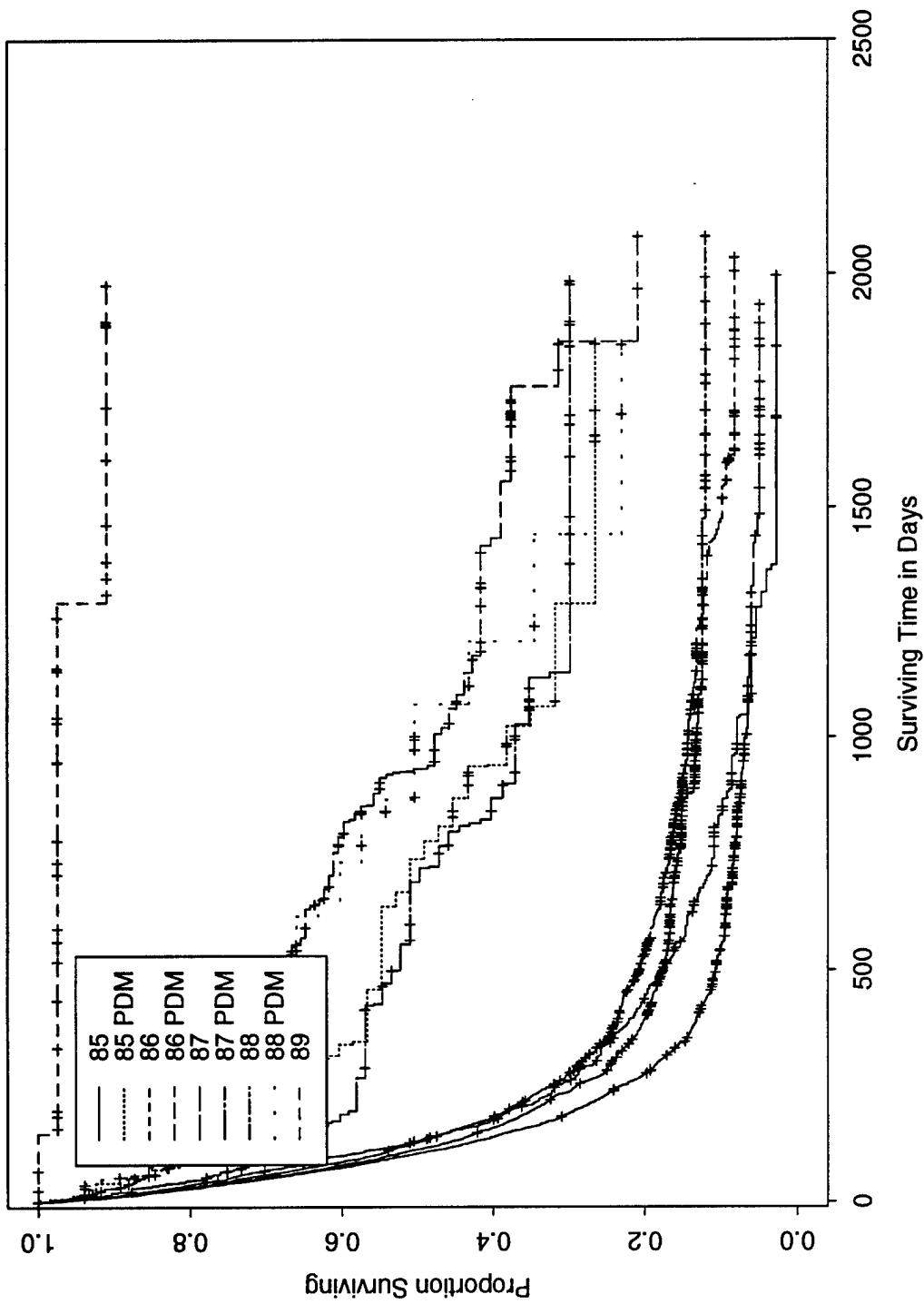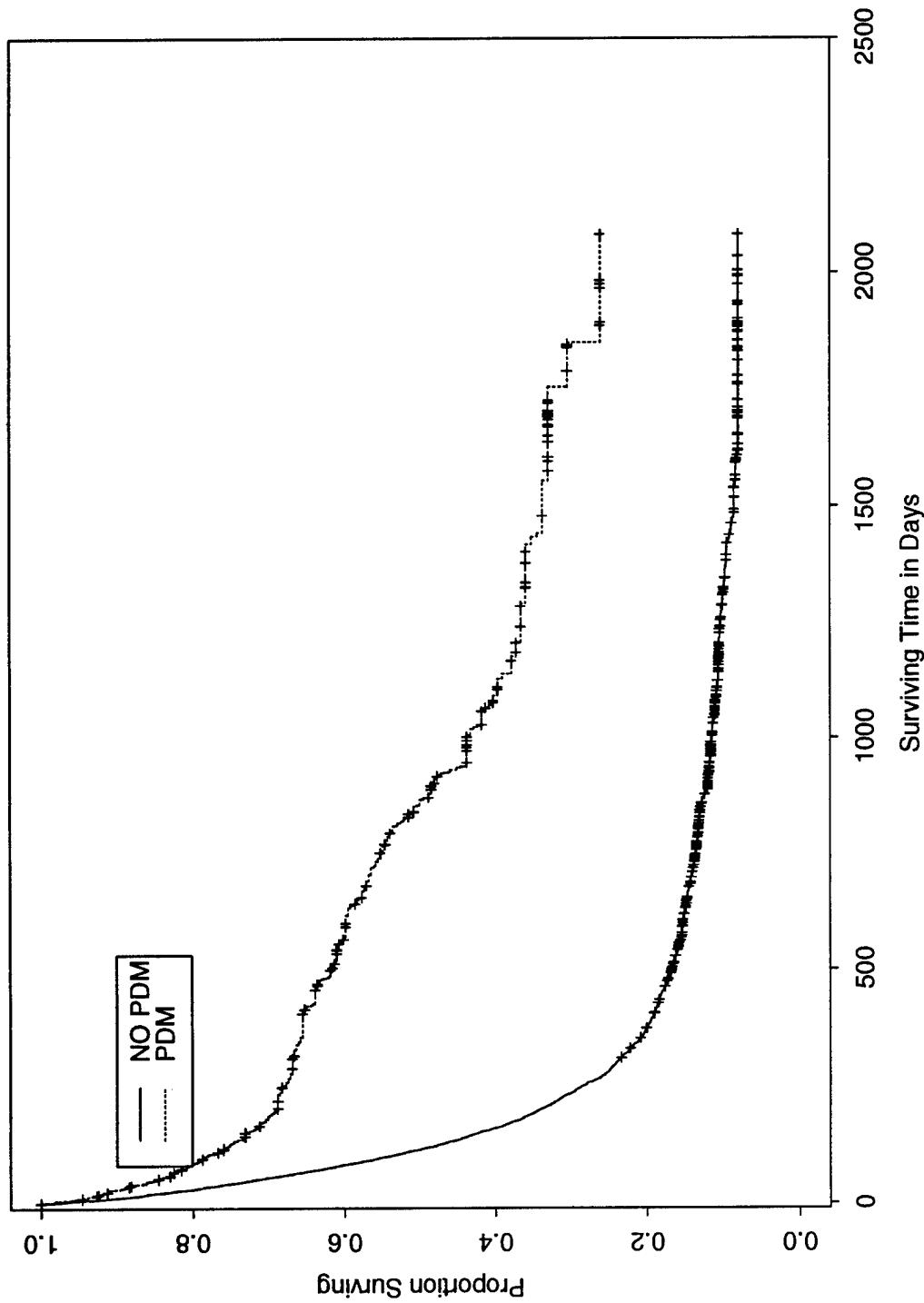
PDM vs NO PDM

Service Time Curve for the LVS's
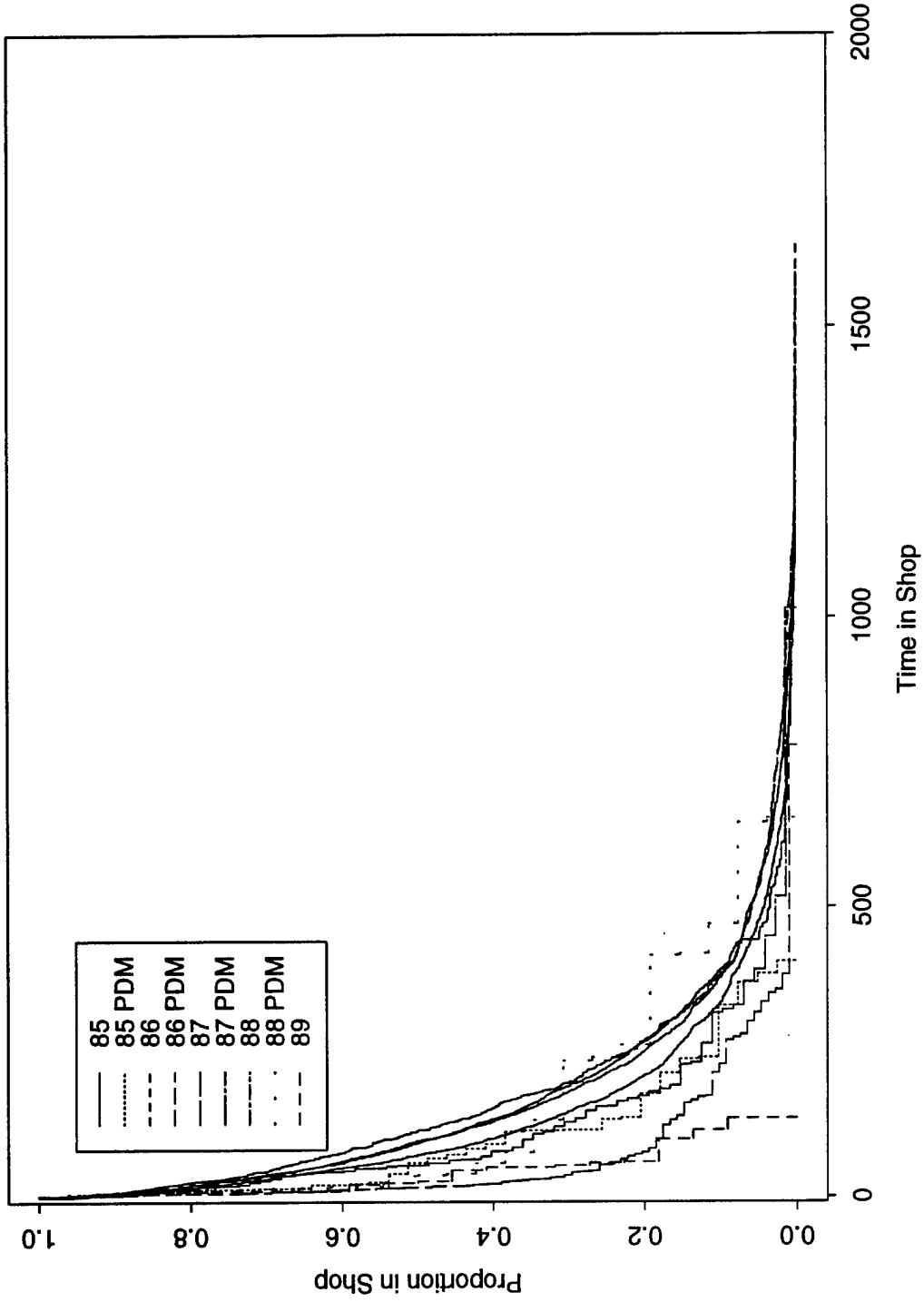
Service Time Curve for PDM vs NO PDM
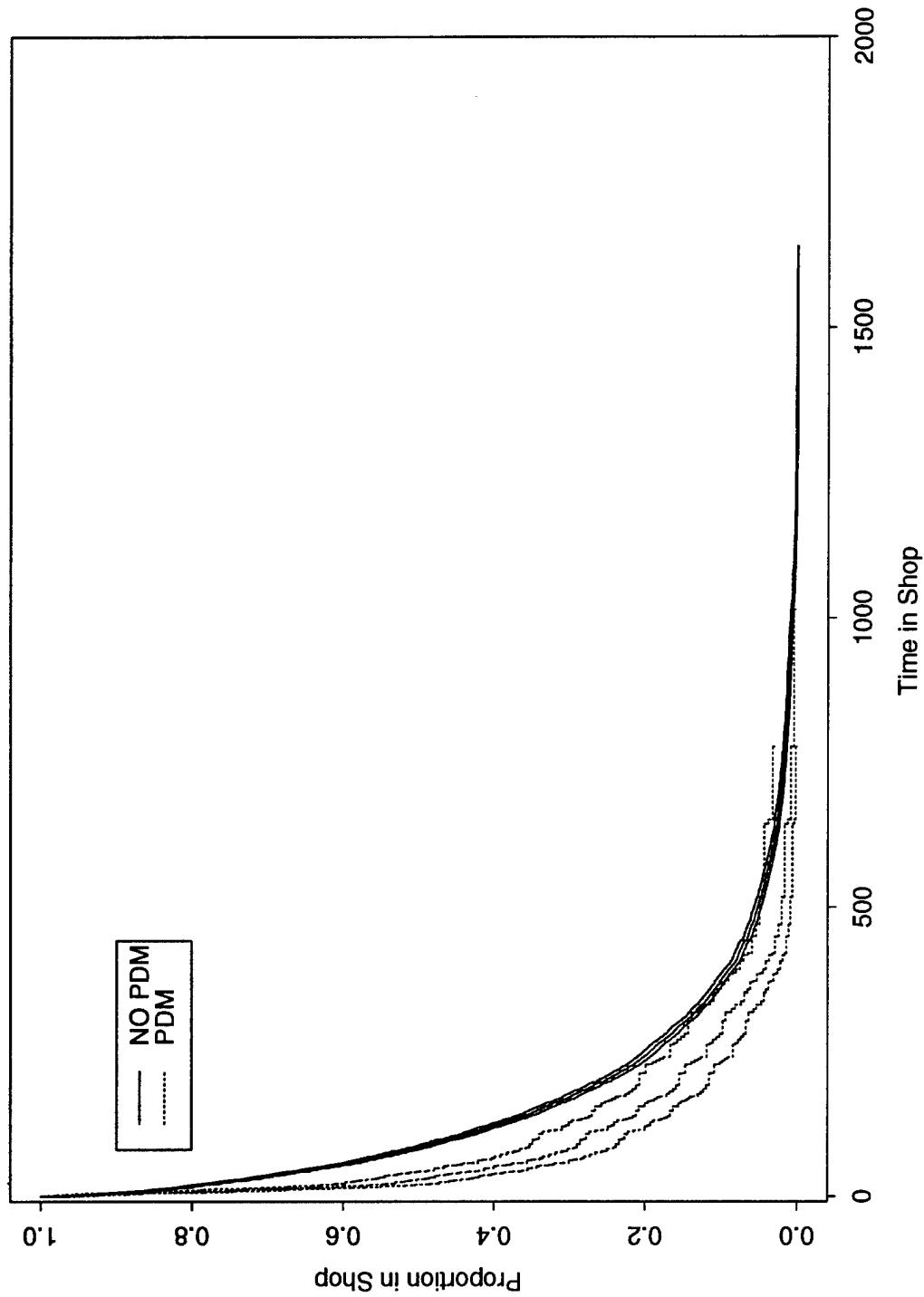
APPENDIX H: 95 Percent Confidence Intervals on Bootstrap Results

Confidence Intervals for Downtime Current Year

GROUP	LOWER Bound	DOWNTIME	UPPER BOUND
85 NO PDM	113.8611	λ	125.3422
85 PDM	37.2219	λ	45.15048
86 NO PDM	109.584	λ	121.2853
86 PDM	15.28309	λ	21.04622
87 NO PDM	128.5612	λ	141.5052
87 PDM	48.17614	λ	57.59184
88 NO PDM	107.5075	λ	118.4825
88 PDM	28.07009	λ	36.25245

Confidence Intervals for Number of Failures per Year

GROUP	LOWER BOUND	FAILURE RATE	UPPER BOUND
85 NO PDM	1.103908	λ	1.195167
85 PDM	0.522451	λ	0.600293
86 NO PDM	1.125237	λ	1.221988
86 PDM	0.325073	λ	0.392322
87 NO PDM	1.381562	λ	1.479826
87 PDM	0.575342	λ	0.664114
88 NO PDM	1.280667	λ	1.386361
88 PDM	0.319051	λ	0.383151

Confidence Intervals for Downtime the Following Year

GROUP	LOWER BOUND	DOWNTIME	UPPER BOUND
85 NO PDM	51.01408	λ	61.68951
85 PDM	11.11369	λ	16.27625
86 NO PDM	53.35083	λ	64.89155
86 PDM	2.538384	λ	5.613546
87 NO PDM	64.49779	λ	76.27161
87 PDM	11.10763	λ	16.82089
88 NO PDM	47.24984	λ	57.9679
88 PDM	14.68874	λ	21.77642

APPENDIX I: Graphs of Bootstrap Results

BOOTSTRAP RESULTS FOR DOWNTIME
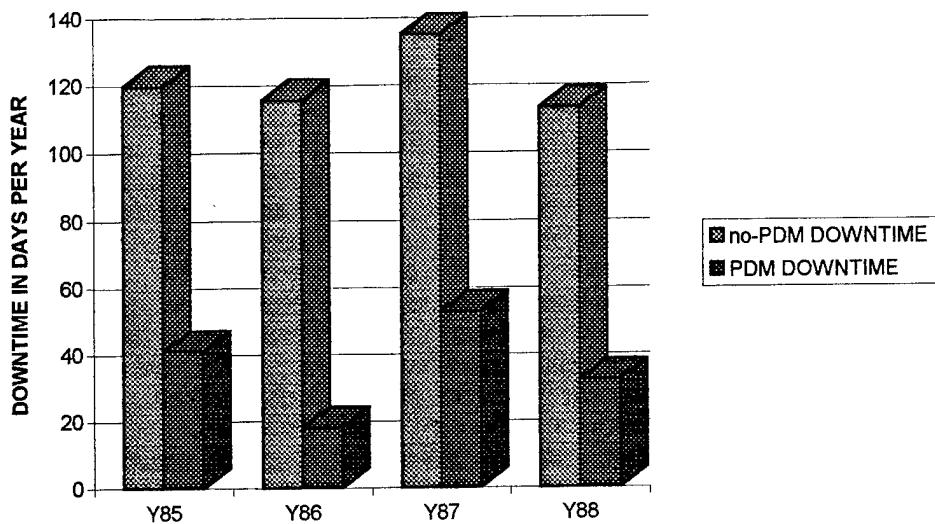
BOOTSTRAP RESULTS FOR FAILURES PER YEAR
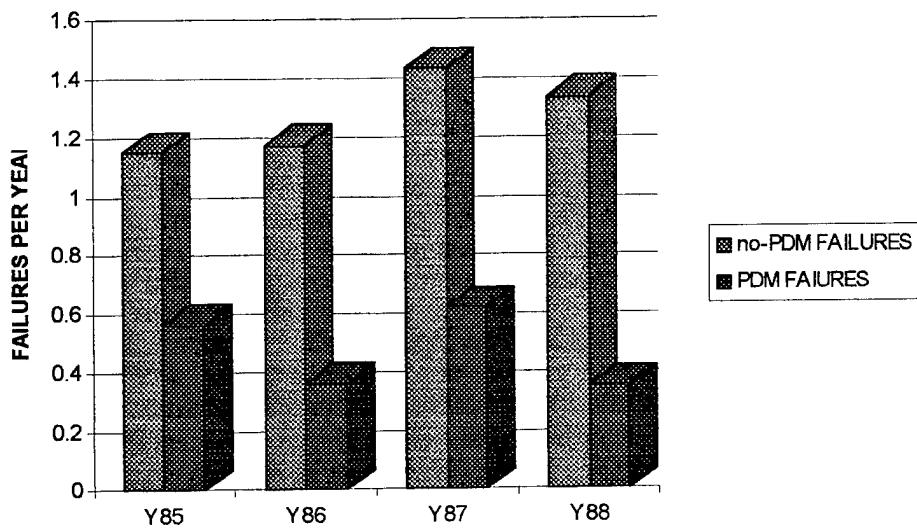
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    Verlag, 1994.

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13. ABSTRACT (Maximum 200 words)

This study used the Poisson regression technique, bootstrap estimates, and the Kaplan-Meier estimates for survivor curves to determine the impact of Programmed Depot Maintenance (PDM) on weapon system availability. More specifically, these techniques estimated the effect in the number failures per year due to PDM, but the bootstrap technique also estimated the effect in the amount of downtime experienced by a weapon system due to PDM. Although the Poisson regression model did not pass the rigors of statistical testing, the Poisson regression suggested differences in the number of failures per year between PDM and no-PDM weapon systems. The results of the bootstrap estimates for the number of failures per year and amount of downtime per year showed that the no-PDM weapon systems experienced approximately 1.3 failures per year while remaining unserviceable approximately 120 days per year, and PDM weapon systems experienced approximately .3 failures per year while remaining unserviceable approximately 30 days per year. PDM reduced the number of failures per year and drastically reduced weapon system downtime per year. PDM increased weapon system availability from approximately 67 percent to approximately 92 percent.

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